Journal of Behavioral and Experimental Finance 20 (2018) 80–91

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

Full length article

The disposition effect does *not* survive disclosure of expected price trends

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ARTICLE INFO

Article history:
Received 23 December 2017
Received in revised form 5 June 2018
Accepted 30 August 2018
Available online 7 September 2018

JEL classification:
G4
G11

Keywords:
Disposition effect
Experimentation
Diversification heuristic

ABSTRACT

The disposition effect (DE) consists in investors' preference for realizing gains over losses. One DE account suggests that this bias stems from a belief in mean-reverting prices. This account, however, was ruled out by Weber and Camerer (1998), who reported a DE when participants were presumably made aware of expected price trends. In two experiments, we revisited this widely cited study (i) by fully disclosing clear and complete information about asset price distributions, and (ii) by assessing the DE on more reliable measures. In Experiment 1, under conditions of full disclosure, a DE was replicated on Weber and Camerer (1998)'s measures but was not found on the more reliable measures. Experiment 2, which was high-powered and offered higher incentives, confirmed these findings. We conclude that the belief in mean-reverting prices cannot be ruled out as a contributing factor to DE. As additional insights, both experiments reveal that participants showed little convergence to optimal portfolio and diversified their portfolios even when diversification was sparsely effective.

1. Introduction

The Disposition Effect (DE hereafter) was coined by Shefrin and Statman (1985). It refers to investors' preference for realizing gains over losses. This behavioral tendency is considered as an investment bias since future performance of assets should be unrelated to their purchase prices. Alongside underdiversification and overtrading, Koestner et al. (2017) refer to the DE as one of the three most widely cited investment mistakes in the literature; one for which the significant negative effect on performance has been well-documented. A large body of research has supported the existence of the DE, and evidence suggests that investors' experience helps to dampen it.[1]

Although numerous studies provided empirical support for the DE, its drivers remain debated. Using trading accounts at a large brokerage house, Odean (1998) found that the DE is not motivated by the desire to rebalance portfolios, tax considerations, or the reluctance to incur high trading costs for low-priced stocks. Such practical causes being dismissed, this work has paved the way for alternative accounts that rely on investors' preferences. A first account relates the DE to Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). This account suggests that decision makers frame their choices in terms of potential gains and losses relative to a reference point. Decisions map onto a S-shaped value function, which is concave in the domain of gains and convex in the domain of losses. Hence, Prospect Theory suggests that individuals are risk-averse in the domain of gains (i.e. they secure their gains) and risk-seeker in the domain of losses (i.e. they keep their losing positions open). Another account asserts that people are reluctant to acknowledge mistakes. When a loser is sold, it is perceived as an irrevocable mistake, while holding it in one's portfolio gives some hope that it may be sold at break-even or even at gain. This phenomenon reflects the tendency to become locked into a costly course of action after an initial investment in money, time or efforts.[2] Finally, the DE may be explained in terms of a belief in mean-reverting prices. According to this account, investors assume that asset prices likely return to less extreme

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[1] The DE was first outlined at the aggregate level, i.e. for a given market or representative groups of investors (Odean, 1998; Shapira and Venezia, 2001; Grinblatt and Keloharju, 2001; Barber et al., 2007). It has then been examined at the individual level, in order to account for heterogeneity across investors as well as the evolution of an individual's behavior over time (Feng and Seasholes, 2005; Dhar and Zhu, 2006; Boolell-Gunesh et al., 2012). The main empirical findings confirm a DE for the average investor and show that both investor's sophistication and trading experience tend to significantly reduce this bias. Some sophisticated investors display even the *reverse* DE (Talpsepp, 2011).

[2] This phenomenon is known under various names such as entrapment (Rubin and Brockner, 1975), sunk cost effect (Arkes and Blumer, 1985) or escalation of commitment (Staw, 1981; Staw and Ross, 1987) and is more generally linked to the theory of cognitive dissonance (Festinger, 1957).

https://doi.org/10.1016/j.jbef.2018.08.003
2214-6350/

values. As a result, they sell winners to avoid a subsequent fall but keep losers while waiting for prices to recover. The latter account is directly relevant to the present research endeavor.

In an influential paper[3] based on an experimental setting, Weber and Camerer (1998) ruled out the belief in mean-reverting prices as a driver of the DE. These authors report that participants keep on falling prey to the DE, even when they are informed that asset prices will show downward, neutral or upward changes, thereby making it unlikely that they still rely on mean-reverting beliefs. To date, the study by Weber and Camerer (1998) is, to the best of our knowledge, the only experimental paper advocating that the mean-reversion explanation does not hold.[4] However, two features of Weber and Camerer (1998)'s study mitigate its interpretation. These relate to the DE measure and to the level of information of participants. Specifically, the DE measure used in that study may have been biased towards producing a DE effect, and the authors may have overestimated how much participants actually knew about the asset price changes. The present study examines these two possibilities and provides empirical support for both.

Regarding the DE measure, Weber and Camerer (1998) assessed the DE of each participant with a coefficient based on the difference in sales of winner and loser assets executed by that participant, normalized by his/her total number of sales. As pointed out by Odean (1998), this approach leads to biased results because of the market trend. Mechanically, one should observe more sales involving a gain than losing sales in an upward market. This is a real issue in Weber and Camerer (1998)'s setting because participants were encouraged to invest in rising assets. In order to better control for the market trend, we should prefer DE measures built on the difference between the proportion of realized gains and the proportion of realized losses.

Turning to uncertainty, Weber and Camerer (1998) report that their participants were well trained statistically and got an accurate impression of the price profile of assets. In particular, they refer to accuracy as a measure called δ, which ranged from 0 (perfect estimates) to 12 (maximally wrong estimates). Their results show that the accuracy of trend estimation varied and decreased in the last investment rounds of the experiment. In their conclusion, the authors acknowledge that some features of their data may be consistent with beliefs in mean-reverting prices and that separating the DE and mean-reversion beliefs more carefully would be worth pursuing in future research. Consistent with the latter note of caution, in a setting adapted from Weber and Camerer (1998) and that combines asset selling with the elicitation of risk preferences and beliefs, Jiao (2017) recently found that the DE is significantly correlated with the belief in mean-reversion but not with the risk attitude parameters of Prospect Theory.

In the present research, we revisited Weber and Camerer (1998)'s experiment by comparing outcomes on the biased DE measures (initially used by Weber and Camerer, 1998) and the unbiased DE measures (based on the proportion of both realized gains and losses). In addition, in Experiment 1, we randomly assigned participants to conditions where they were asked to guess the price distribution of each asset (i.e. replicating the Partial Disclosure condition implemented by Weber and Camerer, 1998) or were fully disclosed the expected price trend of each individual asset (i.e. thereby implementing a Full Disclosure condition). Obtaining a DE on the unbiased measures in the Full Disclosure condition would allow firmly ruling out the belief in mean-reverting prices as a driver of the DE. Contrary to Weber and Camerer (1998), however, we expected to find no such outcome. Specifically, mean-reversion beliefs and Prospect Theory's principles should be largely ineffective when uncertainty is drastically reduced, as it now is under the Full Disclosure condition.

Our results are largely consistent with our expectations. In Experiment 1, when using reliable DE measures, we found no DE, neither in Partial nor in Full Disclosure conditions. Interestingly, a DE on the biased measure was found in the Full Disclosure condition, which supports the view that this measure is sensitive to market trends. Experiment 2 replicates the latter findings, this time focusing on the Full Disclosure condition only, with enhanced power and performance incentives. Consequently, the DE does *not* survive a setting that makes ineffective the belief in mean-reverting prices.

Whereas our main interest was in the effect of disclosure on the DE, in both experiments we also examined participants' convergence to the optimal portfolio, after they were disclosed the price trend of each asset. The optimal strategy for any participant who knows which asset has the highest probability to move up is to immediately buy and hold that asset only. We were interested in the extent to which participants may refrain from doing so. We found that participants preferred to diversify their portfolios even though the benefits of diversification were very limited.

The remainder of this paper is organized as follows. Section 2 focuses on the different DE measures that are used in our analyses. Section 3 describes Experiment 1 and its results are reported in Section 4. Section 5 is devoted to Experiment 2 and Section 6 concludes.

2. Measures of the disposition effect

As mentioned above, the DE is well-established and has been documented in a large number of studies. Most of them report empirical investigations and the study of Weber and Camerer (1998) may be viewed as an original contribution because of their experimental approach. In this paper, the authors measured the DE for each participant using a coefficient based on the difference in sales of winner and loser assets executed by the participant, normalized by his/her total number of sales. This coefficient is then zero if there is no DE and is positive if there is a DE. The problem with that approach is that the coefficient is biased by the market trend. As explained in Odean (1998), sales involving a gain will be automatically more frequently observed than losing sales in an upward market (and vice versa). The coefficient used in Weber and Camerer (1998) to measure the DE is really an issue since their experimental setting encourages participants to invest in rising assets. If participants are able to identify at least some of the rising assets, their market of reference will exhibit an upward trend and their portfolios will consequently deliver more gains than losses, thereby leading to a positive but biased DE.

In order to better control for the impact of the market trend, Odean (1998) recommends to compute the DE as the frequency with which an investor sells winners and losers relative to their opportunities to sell each. In practice, this implies to calculate the difference between the proportion of realized gains and the proportion of realized losses. The latter procedure, which is nowadays recognized as an unbiased analytic approach to the DE, is widely used in the literature. For example, Weber and Welfens (2007) used it to ensure their results would not be affected by a lack of selling opportunities.

To measure the individual-level DE in this paper, we relied on Odean (1998) and achieved the following comparison for each asset held by a participant at a given round. The current price of the asset is compared with its average purchase price to determine

[3] As one of the first studies on the DE, this seminal paper is widely cited in the academic literature. For example, Google Scholar mentions 925 citations, of which some are made in highly-ranked journals such as Journal of Finance, Journal of Financial Economics, Review of Financial Studies, Management Sciences, Journal of Banking and Finance, etc.

[4] In an empirical study, Odean (1998) documents that the belief in mean-reverting prices is unjustified and irrational since the DE leads to lower returns.

whether it is a gain or a loss. If the asset is kept in portfolio, it is considered a *paper* gain or loss. If it is sold, it is considered a *realized* gain or loss. The DE for participant i (DE_i) depends on both his Proportion of Realized Gains (PRG_i) and his Proportion of Realized Losses (PRL_i) as follows:

$$PRG_i = NRG_i/(NRG_i + NPG_i) \tag{1}$$

$$PRL_i = NRL_i/(NRL_i + NPL_i) \tag{2}$$

$$DE_i = PRG_i - PRL_i \tag{3}$$

We should stress that we need that participant i experiences at least one loss and one gain over the investment period since both are necessary to define PRG_i and PRL_i and successfully compute DE_i.

In addition, we replicated the approach of Weber and Camerer (1998) and measured the DE as the difference between realized gains (NRG_i) and realized losses (NRL_i) by participant i normalized by the total number of sales by that participant (NS_i). In order to determine whether the asset is sold for a gain or for a loss, we again compared the selling price to the average purchase price. This DE measure requires that participant i executes at least one sale during the investment period, i.e. NS_i cannot be equal to zero. Although we are aware that this DE measure may be biased because of any market trend, it allowed us comparing our findings for the Partial Disclosure condition to those obtained in a similar condition by Weber and Camerer (1998).

In both approaches, we computed the DE based on trades (DE) but also on the number of traded shares (DE_{shares}) to account for both repurchases and partial sales. We also computed the DE based on the monetary traded volume (DE_{money}) to control for the level of price of assets. Thus, we ended up with three different measures within each approach.

3. Experiment 1

3.1. Setting and procedure

Our setting was adapted from Weber and Camerer (1998) and the experiment was entirely conducted on computers using oTree.[5] All participants were asked to manage online a portfolio of assets, starting with a fictitious budget of 5000 EUR. The experiment counted 10 rounds that gave participants the opportunity to invest this amount (or part of it) in six different assets. Participants were all informed that neither borrowing nor short-selling was allowed and that money held in cash (i.e. not invested) would not bring any interest.

The six available assets (called A, B, C, D, E and F, respectively) were quoted at prices that were changing randomly from one round to the next one. Asset prices were thus not affected by trading decisions. Similar to Weber and Camerer (1998), a price variation was randomly generated for every asset at the beginning of each round. For each asset, the likelihood that its price increases, decreases or remains overall stable across the rounds, relied on one of the following distributions:

- "+ +": the asset price has 65% chance to rise and 35% chance to fall
- "+" : the asset price has 55% chance to rise and 45% chance to fall
- "0" : the asset price has 50% chance to rise and 50% chance to fall
- "−" : the asset price has 45% chance to rise and 55% chance to fall
- "− −": the asset price has 35% chance to rise and 65% chance to fall.

Up to round 4, the existence of the above statistical distributions for the six assets were known by all participants. However, they did not know exactly which distribution drives the prices of which asset. In other words, they did not have a direct correspondence between the assets (A, B, C, D, E and F) and the available price distributions. They only knew there were two assets with prices generated by a "0"-type distribution (prices have equal chances to rise or to fall) and only one asset for each of the four other distributions. Whatever the asset, the magnitude of the price variation at each round was equal to 1, 3 or 5 EUR with equal probabilities ($p = 1/3$). In each round, two draws were used to determine the price variation of a given asset: the first draw allowed setting the change direction (up or down) while the second determined its magnitude (1, 3 or 5 EUR). Draws were independent across assets. Fig. 1 exhibits the empirical prices obtained for the six assets over the whole experiment.

At round 1, participants could observe the six asset prices for four previous hypothetical rounds, namely from round -3 to 0. Those prices are available in a table, wherein assets are displayed in rows and rounds in columns. The purpose was to provide them with historical price information and to help them infer the price sequences with more ups and downs right from the start.[6] In the instructions available in Fig. 2, we stressed the importance to figure out which asset is associated with which price distribution in order to increase portfolio performance.

At each round, participants could trade at market prices, and information about each asset in their portfolio was displayed on their computer screens. In particular, the evolution of asset prices was updated at each round, so that both past and current prices for each asset were summarized in a table. Moreover, for each asset, participants directly observed the number of shares held in portfolio as well as its average purchase price, its current market price, and the resulting paper gain or loss. Both current portfolio value and the amount of available cash were also provided. Participants had no time constraint for making their decisions during a round, i.e. they could take all the time they needed. Fig. 3 illustrates a computer screen for an investment decision at round 2.

Right from the start, participants were randomly assigned to one of the two experimental conditions. Participants in the first condition (Partial Disclosure; replicating Weber and Camerer, 1998) were asked at round 5 to estimate which price distribution was associated with which asset. Those in the second condition (Full Disclosure) received at round 5 clear and correct information about the price distribution of each of the six assets. Fig. 4 shows how information about price distributions was communicated to the participants in this Full Disclosure condition. After their last trading decision at round 10, participants in the Full Disclosure condition were also asked to indicate their confidence in the received information on a scale ranging from 1 to 7.[7]

At the end of the experiment (i.e. at round 11), all the assets held in portfolios were sold at market prices without any trading decision to be made by participants and their final wealth was calculated. All participants were rewarded by a fixed amount of 4 GBP and, for those who scored in the top 10% wealth performance in each experimental condition, an additional reward of 2 GBP was allocated.[8]

5 See Chen et al. (2016) for more details.

6 Without information about the real probability underlying each asset, participants could derive simple probability estimators by counting the number of ups and dividing it by the number of rounds.

7 At round 5, participants in the Full Disclosure condition were also informed that there was no trap in the information about the price distributions and that it really showed how the asset prices have been generated and will continue to be generated during the next rounds. This question about their confidence allowed getting a measure of participants' trust that can be used to assess the consistency between what participants believed and which assets they traded.

8 Monetary incentives were paid in GBP because the experiment was performed through the https://www.prolific.ac/ Prolific Academic platform.

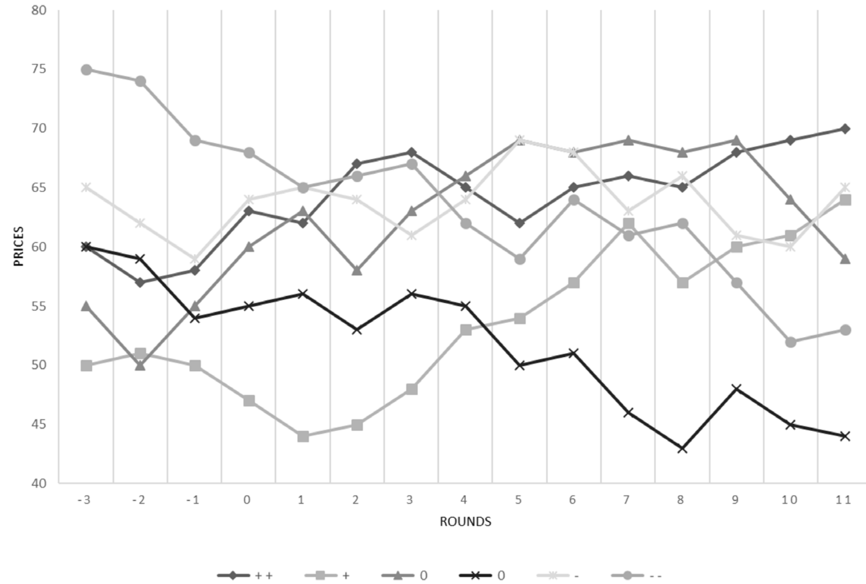
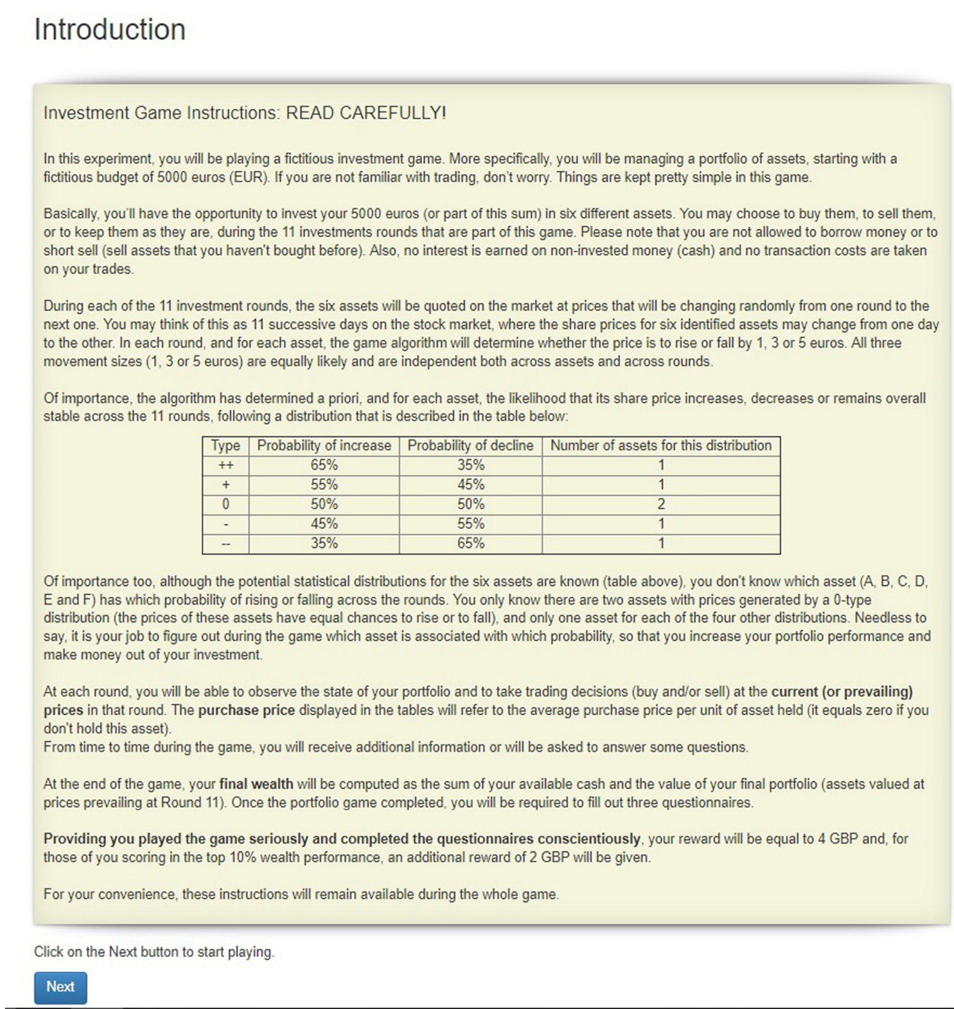


Fig. 1. Price evolution for the six assets.



Introduction

Investment Game Instructions: READ CAREFULLY!

In this experiment, you will be playing a fictitious investment game. More specifically, you will be managing a portfolio of assets, starting with a fictitious budget of 5000 euros (EUR). If you are not familiar with trading, don't worry. Things are kept pretty simple in this game.

Basically, you'll have the opportunity to invest your 5000 euros (or part of this sum) in six different assets. You may choose to buy them, to sell them, or to keep them as they are, during the 11 investments rounds that are part of this game. Please note that you are not allowed to borrow money or to short sell (sell assets that you haven't bought before). Also, no interest is earned on non-invested money (cash) and no transaction costs are taken on your trades.

During each of the 11 investment rounds, the six assets will be quoted on the market at prices that will be changing randomly from one round to the next one. You may think of this as 11 successive days on the stock market, where the share prices for six identified assets may change from one day to the other. In each round, and for each asset, the game algorithm will determine whether the price is to rise or fall by 1, 3 or 5 euros. All three movement sizes (1, 3 or 5 euros) are equally likely and are independent both across assets and across rounds.

Of importance, the algorithm has determined a priori, and for each asset, the likelihood that its share price increases, decreases or remains overall stable across the 11 rounds, following a distribution that is described in the table below:

Type	Probability of increase	Probability of decline	Number of assets for this distribution
++	65%	35%	1
+	55%	45%	1
0	50%	50%	2
-	45%	55%	1
--	35%	65%	1

Of importance too, although the potential statistical distributions for the six assets are known (table above), you don't know which asset (A, B, C, D, E and F) has which probability of rising or falling across the rounds. You only know there are two assets with prices generated by a 0-type distribution (the prices of these assets have equal chances to rise or to fall), and only one asset for each of the four other distributions. Needless to say, it is your job to figure out during the game which asset is associated with which probability, so that you increase your portfolio performance and make money out of your investment.

At each round, you will be able to observe the state of your portfolio and to take trading decisions (buy and/or sell) at the **current (or prevailing) prices** in that round. The **purchase price** displayed in the tables will refer to the average purchase price per unit of asset held (it equals zero if you don't hold this asset).
From time to time during the game, you will receive additional information or will be asked to answer some questions.

At the end of the game, your **final wealth** will be computed as the sum of your available cash and the value of your final portfolio (assets valued at prices prevailing at Round 11). Once the portfolio game completed, you will be required to fill out three questionnaires.

Providing you played the game seriously and completed the questionnaires conscientiously, your reward will be equal to 4 GBP and, for those of you scoring in the top 10% wealth performance, an additional reward of 2 GBP will be given.

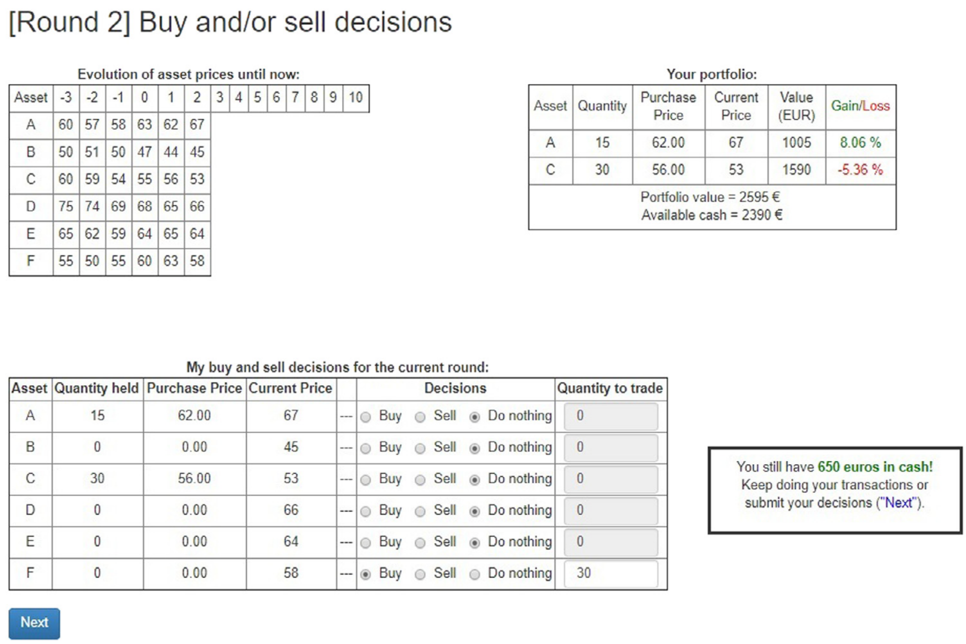
For your convenience, these instructions will remain available during the whole game.

Click on the Next button to start playing.

Next

Fig. 2. Computer screen for the instructions.

We should mention that this initial experiment included several personality questionnaires (such as the Big 5 or the Need for cognition). Participants were requested to fill them in at the end of the investment task. Our objective was to identify potential


[Round 2] Buy and/or sell decisions

Evolution of asset prices until now:

Asset	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
A	60	57	58	63	62	67								
B	50	51	50	47	44	45								
C	60	59	54	55	56	53								
D	75	74	69	68	65	66								
E	65	62	59	64	65	64								
F	55	50	55	60	63	58								

Your portfolio:

Asset	Quantity	Purchase Price	Current Price	Value (EUR)	Gain/Loss
A	15	62.00	67	1005	8.06 %
C	30	56.00	53	1590	-5.36 %

Portfolio value = 2595 €
Available cash = 2390 €

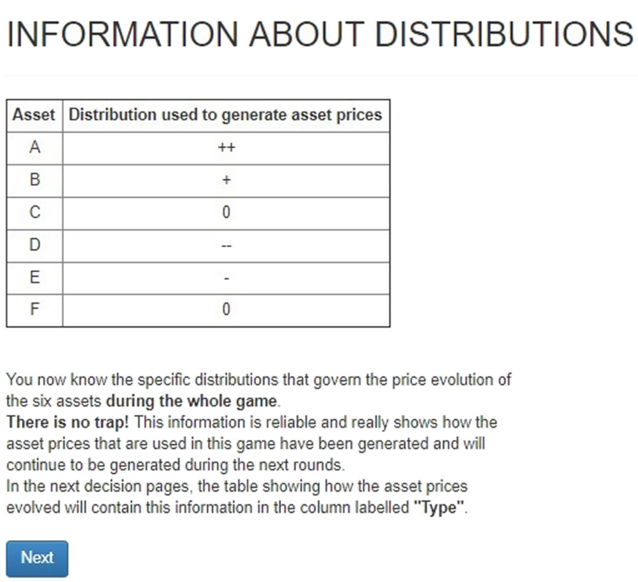
My buy and sell decisions for the current round:

Asset	Quantity held	Purchase Price	Current Price	Decisions	Quantity to trade
A	15	62.00	67	--- Buy Sell Do nothing	0
B	0	0.00	45	--- Buy Sell Do nothing	0
C	30	56.00	53	--- Buy Sell Do nothing	0
D	0	0.00	66	--- Buy Sell Do nothing	0
E	0	0.00	64	--- Buy Sell Do nothing	0
F	0	0.00	58	--- Buy Sell Do nothing	30

You still have 650 euros in cash! Keep doing your transactions or submit your decisions ("Next").

Next

Fig. 3. Computer screen for decision making at round 2.


INFORMATION ABOUT DISTRIBUTIONS

Asset	Distribution used to generate asset prices
A	++
B	+
C	0
D	--
E	-
F	0

You now know the specific distributions that govern the price evolution of the six assets **during the whole game**.
There is no trap! This information is reliable and really shows how the asset prices that are used in this game have been generated and will continue to be generated during the next rounds.
In the next decision pages, the table showing how the asset prices evolved will contain this information in the column labelled **"Type"**.

Next

Fig. 4. Information about the price distributions.

relationships between individual characteristics of participants and their DE. Responses to these questionnaires did not bring relevant information and will not be discussed further.

3.2. Participants

We recruited participants through Prolific Academic. Crowdsourcing platforms have enjoyed a growing success in recent years for various research purposes and are now recognized as a reliable and cost-effective source of high-quality and representative data.[9] Experiment 1 was conducted in November 2016. On the Prolific Academic platform, we used a pre-screening process, which filtered in participants aged between 18 and 75, native in English, holding at least one undergraduate degree, and having already invested in common stocks. A total of 100 participants took part in this first experiment, but we had to eliminate six of them because of technical problems.[10] Over 90% participants lived in the UK or the US. 48 participants and 46 participants were randomly assigned to the Partial and Full Disclosure condition, respectively. In both conditions, we had 18 females and the average age ranged from 35 to 38 years. The youngest (oldest) participant was 21 (63) years old.

Panel A of Table 1 reports statistics about trading activity and performance across all participants in Experiment 1. The average participant executed about 16 trades over the 10 rounds. About 10 (6) of these trades are purchases (sales). The predominance of purchases is unsurprisingly present when focusing on either the participant who traded the least (only one purchase, no sale) or the one who traded the most (34 trades, among which 25 purchases). These descriptive statistics for trading activity do not really differ when distinguishing the Partial and the Full Disclosure condition. Mean values do not statistically differ at the 10% level and standard deviations are just slightly larger in the Partial Disclosure condition (due to more extreme observations).

When looking at performance across all participants in Experiment 1, we find an average return of 3.63%, with a standard deviation of 8.24%. The minimum return of −16.54% and the maximum return of 35.84% confirm heterogeneity in the sample. Nevertheless, the average return is larger for participants in the Full Disclosure condition (5.89% versus 1.47%). This difference is significant at the 1% level and is consistent with better informed participants due to full disclosure of future price trends in that group. Accordingly, the best performer in the Full Disclosure condition earned a return almost twice as high as the return of the best performer in the Partial Disclosure condition. The opposite phenomenon is even stronger when comparing the worst performer in each condition.

Table 1 also shows in Panel A that participants took on average 63.5 seconds to make their trading decisions for a round. When

9 In particular, Peer et al. (2017) assessed data quality of competitive platforms and concluded that Prolific Academic participants produce data quality higher than or comparable to competitors.

10 They could not perform trading decisions because of a too old internet browser version.

Table 1
For all participants (All) and for participants in each experimental condition, i.e. Partial Disclosure of price trends and Full Disclosure of price trends, this table reports the sample size (*N*) and usual descriptive statistics (mean, standard deviation, minimum, maximum) for the number of trades (*Trades*), the number of purchases (*Buy*), the number of sales (*Sell*), the realized performance expressed in percentage (*Return*), and the average time spent for making trading decisions during any round expressed in seconds (*Duration*). Panel A provides data for Experiment 1 while Panel B refers to Experiment 2. *, **, *** indicate whether the means differ between Partial Disclosure and Full Disclosure condition at the level of 10%, 5%, and 1%, respectively.

Activity and performance							
Condition	N	Statistic	Trades	Buy	Sell	Return	Duration
Panel A: Experiment 1							
All	94	Mean	15.9	10.4	5.5	3.63	63.5
		Std	6.4	4.3	3.0	8.24	32.8
		Min	1.0	1.0	0.0	−16.54	11.2
		Max	34.0	25.0	14.0	35.84	169.8
Partial disclosure	48	Mean	16.2	10.7	5.5	1.47	53.9
		Std	7.3	5.0	3.1	7.75	25.2
		Min	1.0	1.0	0.0	−16.54	11.2
		Max	34.0	25.0	14.0	18.80	129.1
Full disclosure	46	Mean	15.7	10.1	5.6	5.89^{***}	73.5^{***}
		Std	5.3	3.3	3.0	8.20	36.8
		Min	4.0	3.0	1.0	−5.06	24.7
		Max	27.0	16.0	14.0	35.84	169.8
Panel B: Experiment 2							
Full disclosure	178	Mean	13.9	9.5	4.4	4.56	54.3
		Std	7.2	4.8	3.0	8.81	33.0
		Min	2.0	2.0	0.0	−16.08	12.1
		Max	34.0	24.0	14.0	41.04	166.4

comparing the average time spent for a round in each experimental condition, the difference is significant at the 1% level and reveals that participants in the Full Disclosure condition took more time to make their decisions.

Panel A of Table 8 available in Appendix summarizes trading activity per participant across rounds. As expected, we observe both a sharp decrease in purchases and an erratic increase in sales from round 1 to 10, whatever the experimental condition.

4. Results

4.1. Disposition effect

Our results for the different measures of DE are provided in Table 2.[11] Panel A0 shows the DE values averaged across all participants in Experiment 1. The three versions of Weber and Camerer (1998)'s measure exhibit a positive and significant DE, ranging from 0.1394 to 0.1615. In contrast, the unbiased measures never deliver a DE that statistically differs from zero. Panel A1 displays the results for the Partial Disclosure condition while the results for the Full Disclosure condition are reported in Panel A2. Comparing results between both conditions, DE values in Panel A1 do not statistically differ from corresponding values in Panel A2. Whatever the measure used, the DE never statistically differs from zero for participants in the Partial Disclosure condition. Our results are however different for participants in the Full Disclosure condition: we find a positive and significant (at the 10% level) DE with the Weber and Camerer (1998)'s approach when using either the number of trades or the monetary traded volume, while the unbiased measures do not provide any significant DE.

At first sight, the outcomes of Experiment 1 may appear counterintuitive when focusing on the Weber and Camerer (1998)'s measures since we observe a positive DE for the subsample of participants who were given clear and correct information about expected price trends. This is hardly surprising, however, considering the sensitivity of Weber and Camerer (1998)'s approach to market trends. Specifically, because participants were encouraged and generally able to identify rising stocks in the experiment, their market of reference had an upward trend and their portfolios tended to contain more gains than losses, thereby producing the illusion of a DE on Weber and Camerer (1998)'s biased measures. When unbiased measures are used, no significant DE is observed in neither of the two conditions.

Table 2
This table reports our results for the different measures of DE. 'Our measure' is based on the difference between the proportion of realized gains and the proportion of realized losses (see Eq. (3)). 'Weber-Camerer98' is built on the difference in realized gains and realized losses, normalized by the total number of sales. *N* gives the number of participants for who we could successfully compute the corresponding DE measure in each experiment or condition. DE, DE_{shares} and DE_{money} give the average DE using the number of trades, the number of traded shares, and the monetary traded volume, respectively. Corresponding DE are also provided in brackets for the best performer (left side) and the worst performer (right side). *, **, *** indicate whether the average DE differs from zero at the level of 10%, 5%, and 1%, respectively. Panels A0, A1 and A2 provide data for Experiment 1 while Panel B refers to Experiment 2. DE values in Panel A1 do not statistically differ from corresponding values in Panel A2 at the 10% level. DE values in Panel A2 do not statistically differ from corresponding values in Panel B at the 10% level.

Disposition effect				
DE measure	N	DE	DE_{shares}	DE_{money}
Panel A0: Experiment 1				
Our measure	93	0.0572	0.0440	0.0463
Weber-Camerer98	92	0.1394^{*}	0.1404^{*}	0.1615^{**}
Panel A1: Experiment 1 - Partial Disclosure				
Our measure	48	0.0811	0.0817	0.0829
		(−0.75,0.10)	(−0.70,0.03)	(−0.70,0.03)
Weber-Camerer98	46	0.1079	0.1199	0.1328
		(−1.00,1.00)	(−1.00,1.00)	(−1.00,1.00)
Panel A2: Experiment 1 - Full Disclosure				
Our measure	45	0.0316	0.0038	0.0073
		(0.31,0.74)	(0.06,0.45)	(0.06,0.45)
Weber-Camerer98	46	0.1708^{*}	0.1609	0.1902^{*}
		(1.00,0.50)	(1.00,0.32)	(1.00,0.42)
Panel B: Experiment 2 (Full Disclosure)				
Our measure	176	−0.0118	−0.0322	−0.0303
		(0.06,0.50)	(0.01,0.43)	(0.01,0.35)
Weber-Camerer98	170	0.1275^{**}	0.1406^{**}	0.1617^{***}
		(1.00,1.00)	(1.00,1.00)	(1.00,1.00)

[11] A few participants had to be left out of analyzes because we could not compute their DE measures because of an absence of (realized) gain or loss.

Table 3
For each experimental condition, this table reports the usual descriptive statistics (mean, standard deviation, minimum, maximum) for different variables aiming at characterizing the behavior of participants. $Wealth_{11}$ refers to the final wealth of each participant at round 11. $Dist_5$ and $Dist_{10}$ assess the gap between the actual guess made by each participant and the optimal guess, at round 5 and round 10, respectively. This gap ranges from 0 (perfect estimate) to 18 (maximally wrong estimate). $Consistency_5$ is a proxy for how consistent trading decisions are with information guessed or received on price distributions. It is computed as a ratio of $ECG_{Ptf,i,5}$ to $ECG_{Opt,i,5}$ and is expressed in percentage (see Eqs. (5) and (4)). *Confidence* refers to the confidence level (ranging from 1 to 7) given by each participant about the received information on price distributions. *N* provides the number of participants in each experiment or condition. Panel A provides data for Experiment 1 while Panel B refers to Experiment 2. In panel A, *** indicates that the average $Wealth_{11}$ in the Full disclosure condition does statistically differ from the corresponding value in the Partial disclosure condition at the 1% level.

Coherence							
Condition	N	Statistic	$Wealth_{11}$	$Dist_5$	$Dist_{10}$	$Consistency_5$	Confidence
Panel A: Experiment 1							
Partial disclosure	48	Mean	5074	4.56	4.40	20.30	.
		Std	388	3.04	2.83	50.47	.
		Min	4173	0.00	0.00	−141.2	.
		Max	5940	14.00	16.00	114.29	.
Full disclosure	46	Mean	5294***	.	.	20.87	5.3
		Std	410	.	.	33.13	1.7
		Min	4747	.	.	−37.80	1.0
		Max	6792	.	.	85.60	7.0
Panel B: Experiment 2 (Full disclosure)							
Full disclosure	178	Mean	5228	.	.	24.66	5.1
		Std	440	.	.	38.38	1.5
		Min	4196	.	.	−105.3	1.0
		Max	7052	.	.	100.00	7.0

We also report in Table 2 the DE values for both the best and worst performer in each condition. In Panel A1, the best (worst) performer always displays a negative (positive) DE, whatever the measure. This phenomenon is still present in Panel A2 but only when considering the unbiased measures. For the Weber and Camerer (1998)'s measures, the best performer exhibits a larger DE than the worst one. Such a result is not consistent with the negative impact of the DE on performance (that is well-documented in the literature) and further confirms that Weber and Camerer (1998)'s measure of DE is not reliable.

4.2. Convergence to optimal portfolio

As explained in the introduction, we took advantage of the data collected here to examine a side question. Specifically, we were interested in how participants would convergence to the optimal portfolio following the price trend disclosure. Clearly, one should witness more convergence in the Full than Partial Disclosure condition. But how good would participants be at converging to the optimal portfolio in the former condition?

We first computed additional variables to assess how participants adapt their strategy and manage their portfolios across rounds. In particular, we first looked at participants' ability to accurately guess price trends in the Partial Disclosure condition. In addition to the final wealth of each participant ($Wealth_{11}$), we computed two variables that capture the gap between the actual guess of each participant and the optimal Bayesian guess, at round 5 ($Dist_5$) and 10 ($Dist_{10}$), respectively. A Bayesian participant should be able to infer from past price variations which asset is likely to follow a given distribution. As in Weber and Camerer (1998), we coded "++" = 2, "+" = l, "0" = 0, "−" = -1, "− −" = -2 in order to build our measure of fit between the best estimate and the actual guess. Then, we summed over the absolute differences between the Bayesian estimate and the participant's actual estimate. The resulting variable ranges from 0 (perfect estimate) to 18 (maximally wrong estimate).[12]

Next, in order to assess to what extent trading decisions were consistent with the information received or guessed about the price distributions, we computed a measure of consistency at round 5, i.e. $Consistency_5$. We may illustrate this with a participant in the Full Disclosure condition who is informed at round 5 that asset B is the most promising asset ("++"-type distribution). Accordingly, he/she should sell all other assets and invest in as many shares in asset B as he/she can ($NS_{i,5}$). The resulting portfolio is optimal for that participant since it maximizes his/her expected capital gain ($ECG_{Opt,i,5}$) between rounds 5 and 11, which is computed as follows:

$$ECG_{Opt,i,5} = (0.65 - 0.35) * 3 * 6 * NS_{i,5} \tag{4}$$

On average, the asset with the "++"-type distribution is 30% more likely to rise than to fall during each round and the expected magnitude of each change is 3 EUR. Since there are 6 price variations between rounds 5 and 11, the product of these elements delivers the expected capital gain of one share of the asset with the "++"-type distribution. Multiplying this amount by the maximum number of shares participant *i* could buy ($NS_{i,5}$) gives the expected capital gain of the optimal portfolio.

If $Pos_{i,k,5}$ represents the position held by participant *i* in asset *k* at round 5, one may follow the same approach to compute the expected capital gain of the actual portfolio selected at round 5 by this participant *i*:

$$ECG_{Ptf,i,5} = \sum_k (Prob_k - (1 - Prob_k)) * 3 * 6 * Pos_{i,k,5} \tag{5}$$

In Eq. (5), the first term of the product (difference of probabilities) is equal to zero for a position held in an asset with "0"-type distribution and is negative if the expected variation of asset prices is negative ("−" or "− −"). Our $Consistency_5$ variable is then simply the ratio of $ECG_{Ptf,i,5}$ to $ECG_{Opt,i,5}$. For example, a value of 0.85 means that the actual portfolio is close to the optimal one, although it may be further improved. Its expected capital gain is 85% of the optimal one.

For participants in the Partial Disclosure condition, who were asked to guess the price distributions at round 5, we use both Eqs. (4) and (5) but after having replaced the actual probabilities ($Prob_k$) with what the participant guessed. Indeed, if he/she

12 Since Weber and Camerer (1998) constrained their subjects to associate a "0"-type distribution with two different assets only and each of the other distributions to only one asset, the maximum value of their measures is 12. Because we did not put any constraint when participants were requested to guess the price distributions, our maximum value is 18.

Table 4
This table reports the results obtained by regressing individual DE on several variables and an intercept. *Our measure* is based on the difference between the proportion of realized gains and the proportion of realized losses (see Eq. (3)). *Weber − Camerer*98 is built on the difference in realized gains and realized losses, normalized by the total number of sales. Both DE measures are computed using the number of trades. 'Gender' equals 1 for men. 'Age' is the participant age at the time of the experiment. 'Consistency' is a proxy for how consistent trading decisions are with information guessed or received on price distributions at round 5. It is computed as a ratio of $ECG_{Ptf,i,5}$ to $ECG_{Opt,i,5}$ and is expressed in percentage (see Eqs. (5) and (4)). 'Confidence' refers to the confidence level (ranging from 1 to 7) given by each participant about the received information on price distributions. *, **, *** indicate statistical significance at the level of respectively 10%, 5%, or 1%.

Regression		
	Our measure	*Weber-Camerer*98
Panel A1: Experiment 1 - Partial Disclosure		
Intercept	−0.1066	−0.2334
Gender	0.0440	−0.0760
Age	0.0065	0.0143
Consistency	−0.0034**	−0.0060**
Panel A2: Experiment 1 - Full Disclosure		
Intercept	0.0485	0.0819
Gender	−0.0196	−0.1057
Age	0.0002	0.0046
Consistency	−0.0042***	−0.0050
Confidence	0.0142	0.0139
Panel B: Experiment 2 (Full Disclosure)		
Intercept	0.4302***	0.8653***
Gender	0.0608	0.1646
Age	−0.0059**	−0.0106**
Consistency	−0.0024***	−0.0050***
Confidence	−0.0405**	−0.0637*

mistakenly associated asset D (instead of asset B) with the "++"-type distribution, we consider that the probability of a rise for asset D is 65% and that it is very consistent to invest all he/she can in that asset D. This allows us focusing on the consistency of participants' trading decisions, no matter whether they were right or wrong in their guesses. For participants in the Full Disclosure condition, we additionally consider their confidence level in the received information, which is scaled from 1 (low confidence) to 7 (high confidence).

Results for the above variables are reported in Panel A of Table 3. The average final wealth of participants ($Wealth_{11}$) is higher in the Full Disclosure condition (5294 versus 5074, with a statistical difference at the 1% level). This observation also holds for both the minimum and the maximum values, which is consistent with better informed participants due to the full disclosure of future price trends. As for the accuracy of estimation in the Partial Disclosure condition, we obtain an average of 4.56 at round 5 and 4.40 at round 10. Both values are close and the standard deviation is somewhat lower at round 10, probably due to a decrease of uncertainty (since more historical asset prices are available at round 10 than at round 5). When focusing on trading consistency at round 5, we find that the average portfolio expected capital gain is about 20% of the optimal portfolio in both groups. This result seems surprisingly low, in particular for participants in the Full Disclosure condition. Although they knew which asset had the highest probability to move up (the average confidence level is equal to 5.3, suggesting they tended to trust the received information), they did not immediately adjust their portfolios in favor of that asset. The standard deviation, however, is lower in the Full Disclosure condition, which suggests less heterogeneity across behaviors in this group of participants.

As complementary analysis, we regressed the individual DE on a set of explanatory variables including an intercept, gender and age as usual control variables and our $Consistency_5$ variable. For participants in the Full Disclosure condition, we also added their confidence level in the received information (*Confidence*). Results are reported in Table 4, in Panel A1 (A2) for the Partial (Full) Disclosure condition. Coefficient estimates for age and gender are never significant. In Panel A1, we observe a negative relationship between the DE and consistency at the 5% level, whatever the DE measure used as dependent variable. In Panel A2, this relationship is even statistically significant at the 1% level but only for the unbiased DE measure. As for the participant's confidence level in the received information, we find no significant relationship with the DE in the Full Disclosure condition of Experiment 1.

Building on the above result showing a low consistency between trading decisions and expected price trends, we examined whether and how participants in the Full Disclosure condition converged to the optimal portfolio, since they knew exactly which asset was most promising ("++"-type distribution). Because the value of diversification is very limited in our experimental setting,[13] the optimal strategy for any participant who knows which asset has the highest probability to move up is to buy and hold this asset only. We then define two variables to characterize a participant's investment intensity in the most promising asset across rounds. First, we measure $WealthIntensity_t$ as a ratio of the value of the position held in the "++"-type asset at round t to the total wealth available at round t. A rational Bayesian subject should invest all his/her wealth in that asset and his/her ratio should be equal or very close to 100%. Second, we define $PortfolioIntensity_t$ as a ratio of the value of the position held in the "++"-type asset at round t to the total portfolio value (excluding cash) at round t.

Panel A of Table 5 reports the evolution of the two above variables aiming at characterizing participants' investment intensity in the most promising asset from round 4 to 10. Both variables doubled from round 4 to 5, showing that participants increased the weight invested in the most promising asset just after having received information about price distributions. However, this adjustment did not lead to the optimal portfolio: the average $WealthIntensity_5$ is about 25% and the average $PortfolioIntensity_5$ is about 28%, which is quite far from 100% in both cases. For the next rounds, both variables fluctuate a little bit but are still much lower than the expected target of 100%. For example, at round 10, the portfolio weight invested in the "++"-type asset averages only 30%. This reveals that, even when they know which asset has the highest probability to move up, participants do not choose to invest all their money in that asset. They appear to prefer to hold a diversified portfolio despite the fact that our experimental design makes the benefits of diversification sparsely effective. This finding is consistent with Weber and Camerer (1998) who report that their participants held a more diversified portfolio, and traded more often, than was optimal.

In Panel A of Table 5, we also report the correlations between the investment intensity in the most promising asset computed in monetary value ($WealthIntensity_t$) and the confidence level given by participants at round 10. These correlations are the highest from round 5 to 8 and tend to decrease in the last rounds. This could suggest that participants mainly adapt their strategy in the short-run and that the impact of the received information decreases afterwards. When looking at the correlations between the investment intensity in the most promising asset computed in monetary value either at round 5 or 10 ($WealthIntensity_5$ or $WealthIntensity_{10}$) and the DE, we observe negative values, whatever the DE measure. This is consistent with the expected negative relationship between the optimal strategy and the DE.

5. Experiment 2

Experiment 1 found evidence supportive of a DE only on biased measures. Hence, the DE does not seem to survive disclosure

13 In comparison with a portfolio including only the asset "++", a portfolio equally invested in both asset "++" and asset "+" can reach a lower variance but at the cost of a lower expected return. Furthermore, this portfolio will have a probability of loss higher than 35%.

Table 5
For participants in the Full Disclosure condition, this table reports information about the investment intensity in the most promising asset ("++"-type distribution). $WealthIntensity_t$ is measured by dividing the value of the position in the "++"-type asset at round t by the wealth available at round t. $PortfolioIntensity_t$ is a ratio of the value of the position held in the "++"-type asset at round t to the total portfolio value (excluding cash) at round t. Panel A provides data for Experiment 1 while Panel B refers to Experiment 2. The last three rows in both panels provides the correlations of $WealthIntensity_t$ with the confidence level (*Confidence*) that participants give to information about price distributions they received at round 5 as well as with the DE measures. For the latter, we only report correlations with $WealthIntensity_5$ and $WealthIntensity_{10}$. *Our measure* is based on the difference between the proportion of realized gains and the proportion of realized losses (see Eq. (3)). *Weber − Camerer*98 is built on the difference in realized gains and realized losses, normalized by the total number of sales. Both DE measures are computed using the number of trades. All variables are expressed in percentage.

Convergence to optimal portfolio							
$Round_t$	4	5	6	7	8	9	10
Panel A: Experiment 1							
$Wealth\ Intensity_t$	12.81	25.11	27.52	25.74	24.27	23.97	25.40
$Portfolio\ Intensity_t$	14.91	28.09	32.48	30.46	28.19	29.00	30.01
Correlations with Confidence	0.19	30.13	35.41	34.05	30.24	22.23	18.19
Correlations with DE (Our measure)	–	−0.28	–	–	–	–	−0.42
Correlations with DE (Weber-Camerer98)	–	−0.14	–	–	–	–	−0.30
Panel B: Experiment 2							
$Wealth\ Intensity_t$	14.92	28.88	33.51	33.46	34.59	33.74	32.96
$Portfolio\ Intensity_t$	19.02	35.91	40.36	39.73	39.79	38.16	37.28
Correlations with Confidence	0.12	34.02	38.73	41.53	42.02	41.58	44.15
Correlations with DE (Our measure)	–	−0.17	–	–	–	–	−0.30
Correlations with DE (Weber-Camerer98)	–	−0.25	–	–	–	–	−0.34

of expected price trends, even when disclosure is only partly achieved. Two limitations may have contributed to this outcome, though. Firstly, findings could be attributed to a lack of power for detecting a small but true DE. Secondly, incentives could have been insufficient to fully involve participants in the investment task. We decided to overcome these limitations in a large sample size follow-up study wherein all participants were assigned to the Full Disclosure condition, i.e. they were all given all individual expected price trends at round 5.

This second experiment was conducted in April 2017. We defined a larger sample size with a power test. For that purpose, we used the statistically significant DE based on Weber and Camerer (1998)'s measures (see results from Panel A2 in Table 2) and assumed a mean DE of 16% and a standard deviation of 0.7, with a nominal power of 90%. The result led to a minimum size of 166 subjects. We decided to target 180 participants in order to accommodate for potential data loss. To bolster their involvement in the investment task, we also increased monetary incentives: all participants were still rewarded with a fixed amount of 1.7 GBP[14] but the three best performers received an additional amount of 20, 10, and 5 GBP, respectively. By multiplying the variable incentive by 10, 5 and 2.5 for the first, second and third performers, we offered larger incentives (although with a lower probability of win). Since we jointly increase sample size and incentives, we cannot disentangle the impact of each adjustment. However, our purpose was not concerned with the latter question. Rather, Experiment 2 was aimed at performing a robustness check for the findings obtained in the Full Disclosure condition in Experiment 1, which implied securing enough power for detecting a small DE effect as well as participants' engagement in the task.

A total of 178 subjects took part in Experiment 2,[15] among which 90 were females. The average age ranged from 34 to 36 years, whatever the gender. The youngest (oldest) participant was 20 (65) years old. The sample of participants in Experiment 2 is very similar to the one in Experiment 1, except for the proportion of females that is larger in the second experiment (51% versus 38%).

Panel B of Table 1 reports statistics about trading activity and performance for Experiment 2. The average participant executed about 14 trades and about 10 (4) of them are purchases (sales). Such a trading activity is very close to what we observed in the Full Disclosure condition of Experiment 1. The average return earned by participants is 4.56%, with a standard deviation of 8.81%. On average, performance is then slightly lower in Experiment 2 than in the corresponding condition of Experiment 1. In particular, the worst performer in Experiment 2 earned a return of −16%. As for the time spent for making decisions, the average participant took on average about 54 seconds for a round in this second experiment. Compared to the Full Disclosure condition of Experiment 1, participants were on average quicker in Experiment 2. Panel B of Table 8 in Appendix provides trading activity per participant across rounds. Like for Experiment 1, we observe both a clear downward trend in purchases and a rather upward trend in sales from rounds 1 to 10.

5.1. Disposition effect

Results for the DE are provided in Panel B of Table 2.[16] All the DE measures built on Weber and Camerer (1998)'s approach are positive and statistically different from zero at the 5% or 1% level. They range from 0.1275 to 0.1617, which appear lower than what we observed in the Full Disclosure condition of Experiment 1. Nevertheless, they do not statistically differ from the corresponding values in Panel A2. Consistent with Experiment 1, when focusing on the unbiased measures, we still find no significant DE. In addition, the unbiased DE values in Panel B do not statistically differ from the corresponding values in Panel A2, suggesting the robustness of the outcomes across Experiment 1 and 2. Panel B also confirms that Weber and Camerer (1998)'s DE measure does not quite discriminate between best and worst performers, whereas the unbiased measures deliver consistent results. Hence, Experiment 2 fully replicates the patterns observed in the previous experiment.

5.2. Convergence to optimal portfolio

The average final wealth for participants is about 5228 EUR (see Table 3), which is not statistically different at the 10% level from

14 The fixed incentive is lower in this follow-up study because we dropped off personality questionnaires at the end of the investment task that were used in Experiment 1 but led to unworkable results. As a result, Experiment 2 was completed much faster.

15 Two participants were eliminated because they did not trade at all.

16 A few participants had to be left out of analyzes because we could not compute their DE measures because of an absence of (realized) gain or loss.

Table 6
This table provides information about the composition of portfolios in Experiment 2. Panel A gives the average number of different assets held by participants at each round. Panel B reports the percentage of participants who hold any asset associated with each available price distribution ("++", "+", …) at each round.

Diversification										
Round$_t$	1	2	3	4	5	6	7	8	9	10
Panel A: Number of assets in portfolio										
	2.80	3.22	3.24	3.16	3.13	2.94	2.75	2.74	2.60	2.48
Panel B: Proportion of participants holding each asset										
++	47.75	55.62	56.74	58.99	77.53	78.09	74.72	75.28	71.35	67.42
+	46.07	55.62	52.81	49.44	57.30	56.74	56.18	62.36	56.18	55.62
0	60.11	59.55	59.55	57.30	52.81	41.57	37.64	36.52	35.39	33.15
0	44.38	51.69	54.49	53.37	54.49	56.18	51.12	47.19	45.51	42.13
−	46.63	50.00	49.44	46.63	29.78	26.97	23.60	20.79	20.22	19.10
−−	34.83	49.44	51.12	50.56	41.01	34.27	31.46	32.02	31.46	30.90

what we observe for participants in the Full Disclosure condition of Experiment 1. The consistency of trading decisions with price trends appears somewhat higher but with a larger dispersion: the average expected capital gain amounts to about 24% of the optimal portfolio and the corresponding standard deviation is equal to 38.38%. As for the confidence level reported by participants, we obtained an average of 5.1, which confirms, like in Experiment 1, that participants generally trusted information about price distributions.

When focusing on the regression results reported in Panel B of Table 4, we observe again a negative relationship between the DE and consistency at the 1% level, whatever the DE measure used as dependent variable. We find a similar result for the participant's confidence level in the received information, at the 5% level for the unbiased DE measure and at the 10% level for the Weber and Camerer (1998)'s DE measure. It is also worth noticing that the relationship between age and DE is significantly negative in this second experiment, which is consistent with the extant literature.

Consistent with Experiment 1, Panel B of Table 5 shows that $WealthIntensity_t$ and $PortfolioIntensity_t$ doubled from round 4 to 5, revealing that participants increased the weight invested in the most promising asset just after having received information about price distributions. In contrast with the results in Panel A, however, both variables keep on slightly increasing across the next rounds to reach larger final values at round 10. The correlations between $WealthIntensity_t$ and confidence level are also higher in Panel B, especially in the last rounds. Results also confirm that participants did not adjust their trading strategy to hold the optimal portfolio: the average $WealthIntensity_{10}$ is about 33% and the average $PortfolioIntensity_{10}$ is about 37%, which is far from 100% in both cases. Like in Experiment 1, we may conclude that participants prefer to diversify their portfolios despite the fact that our experimental design implies very limited benefits of diversification. As expected, the correlations between either $WealthIntensity_5$ or $WealthIntensity_{10}$ and the DE are again negative.

To gain insights on this phenomenon, which may be interpreted as excessive diversification, Table 6 provides information about the composition of portfolios held by participants at each round. Panel A shows that participants held on average 2 or 3 assets across rounds. In Panel B, the proportion of participants who held the most promising asset jumps to 77% at round 5, i.e. just when full disclosure is achieved. This proportion, however, slightly decreases to 67% at round 10. Unsurprisingly, the asset with a "+"-type distribution is also quite popular: 55% of participants held it at round 10. As for the proportion of participants who held the asset with the worst price distribution ("− −"-type), it went down right from round 4 on. However, this asset was still held by about 30% of the participants at round 10.

Table 7 provides additional insights into participants' investment strategies. It reports the numbers of buyers and sellers for each asset at each round, as well as whether the position held in a given round is above (up), below (down) or equal to the position held at the end of round 4, i.e. just before full disclosure is achieved. Three observations emerge from Table 7. First, purchases are generally higher and sales lower on the better assets, which makes perfect sense because of the full disclosure of expected price trends. Second, focusing on shifts between round 4 and 5, participants clearly increase their investment in the best assets and disengage from the worst ones; this is, just after full disclosure is achieved. Third, this rational investment strategy remains suboptimal and is not much improved across the following rounds. Such stability in investment decisions may reflect a status quo bias. As to whether sunk cost effects operated, the present data do not allow supporting or rejecting this interpretation. This is because variations in stability patterns mainly differentiate winners ("++" and "+" assets) versus others ("0", "0","−","− −"), instead of losers ("− −") against others ("0", "0", "+", "++"). In other words, there is no evidence that participants were particularly prone at sticking to their most detrimental investments. Finally, we could assume that overdiversification is partially driven by our experimental setting. Since cash does not bring any interest, participants are encouraged to invest in assets, instead of holding cash. However, this should affect portfolio size rather than the number of different assets held in portfolio. The way final performance is determined and incentives are paid could also have played a role and made participants take some actions only to maximize their final wealth. Since incentives are higher in Experiment 2 but are paid for the three best performers only, they should push participants to take more risks and to focus on fewer stocks. We could also consider that the empirical asset prices used in this study, in particular the fact that the asset that realized the best performance was the one driven by the "+" distribution (and not the "++"), could have impacted trading decisions and indirectly encouraged overdiversification.

6. Conclusion

In two online investment experiments wherein the belief in mean-reverting prices is made ineffective by disclosing expected price trends, we found evidence for a DE on biased measures that are sensitive to market trends. This finding makes sense as participants had the opportunity to make decisions in an upward market of reference (i.e. they could form expectations about or directly identify the expected winners among the available assets). Of importance, however, we systematically failed to observe a DE on unbiased measures, and the latter outcome is hardly attributable to a lack of power in detecting a true DE. Hence, it may be concluded that the DE does not survive expected price trends disclosure. The belief in mean-reverting prices cannot therefore be ruled out as a potential contributor to the DE. Admittedly, this does not imply

Table 7
This table reports the number of buyers ('# buyers') and sellers ('# sellers') among the 178 participants at each round. '# ups', '# downs', and '# equals' gives information about how the position in a given round is above, below or equal to the position held at the end of round 4 (just before receiving information about asset price distributions), respectively. Each panel refers to a given asset.

Sunk cost										
Round$_t$	1	2	3	4	5	6	7	8	9	10
Panel A: '++' Asset										
# buyers	85	60	43	23	90	49	29	21	18	21
# sellers	.	21	14	12	4	9	18	10	21	19
# ups	.	.	.	.	90	105	100	104	97	95
# downs	.	.	.	.	4	9	12	14	21	27
# equals	.	.	.	.	84	64	66	60	60	56
Panel B: '+' Asset										
# buyers	82	45	39	39	52	34	34	28	22	23
#sellers	.	8	18	31	9	16	15	11	17	15
# ups	.	.	.	.	52	62	70	81	76	76
# downs	.	.	.	.	9	18	23	25	30	35
# equals	.	.	.	.	117	98	85	72	72	67
Panel C: '0' Asset										
# buyers	107	24	24	33	13	9	9	5	8	8
# sellers	.	19	18	21	29	30	13	6	8	13
# ups	.	.	.	.	13	16	19	21	21	19
# downs	.	.	.	.	29	52	55	56	57	63
# equals	.	.	.	.	136	110	104	101	100	96
Panel D: '0' Asset										
# buyers	79	32	22	20	22	17	21	18	11	13
# sellers	.	15	10	13	15	10	16	13	10	11
# ups	.	.	.	.	22	36	44	51	50	50
# downs	.	.	.	.	15	23	31	41	43	50
# equals	.	.	.	.	141	119	103	86	85	78
Panel E: '−' Asset										
# buyers	83	19	18	12	12	5	3	1	3	2
# sellers	.	10	31	13	40	10	11	7	6	5
# ups	.	.	.	.	12	13	12	11	12	11
# downs	.	.	.	.	40	48	54	57	61	63
# equals	.	.	.	.	126	117	112	110	105	104
Panel F: '−−' Asset										
# buyers	62	46	19	24	13	8	7	8	10	6
# sellers	.	5	9	15	37	19	13	8	4	9
# ups	.	.	.	.	13	15	14	20	25	24
# downs	.	.	.	.	37	49	56	56	57	57
# equals	.	.	.	.	128	114	108	102	96	97

that this belief drives the DE in real investment settings characterized by more uncertainty. However, such account cannot be excluded based on the experimental rationale developed by Weber and Camerer (1998).

Although not anticipated, another insight of the present research is that participants kept on diversifying their portfolios to a large extent, even though they were informed about (and appeared to be confident in) the expected returns of individual assets. In other words, they preferred to diversify their portfolios even though this strategy was explicitly associated with lower expected returns and a higher probability of loss. This finding was observed in both experiments, and despite enhanced incentives for performance implemented in Experiment 2. This overdiversification might be the result of a status quo bias or any sunk cost effects. It could also be driven by some features of our experimental setting (incentives, empirical prices, etc.). The data at hand do not allow us testing the driver(s) of this effect.

The search for diversification in our setting might also be consistent with the existence of a *diversification heuristic* that may have developmental roots as argued by De Giorgi and Mahmoud (2017). In an experiment testing whether children apply a diversification heuristic in a sequence of hypothetical choice questions and dice-rolling games, these authors reported clear preferences for diversification over concentration, both for the sake of variety and the purpose of mitigating risk. In our experiments, we could consider that participants are reluctant to invest all their money in a single asset for the same reasons, although this asset exhibits the highest expected return. They could prefer to hold a variety of assets to avoid concentration and/or they could aim at reaching a lower variance for their portfolios' returns. This second objective, however, would imply that they are more sensitive to risk defined as volatility (i.e. standard deviation of returns) instead of probability of loss, since any diversification in our setting leads to a probability of loss higher than the probability of loss associated with the most promising asset. Testing whether participants' sensitivity to risk definitions does affect their behavior in an experimental setting as ours may be considered in further research.

Acknowledgments

We thank Oleg Urminsky and Bernd Wittenbrink for their useful comments and suggestions. The authors also thank the anonymous referee who really helped improve the paper. All remaining errors and omissions are the full responsibility of the authors. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of interest

None.

Table 8
For each round, this table reports the average number of purchases (*BUY*) and sales (*SELL*) per participant. These statistics are computed across all participants (All), across participants in the Partial Disclosure condition, and across participants in Full Disclosure condition, respectively. Panel A provides data for Experiment 1 while Panel B refers to Experiment 2.

Activity across rounds						
Round	BUY			SELL		
	All	Partial Disclosure	Full Disclosure	All	Partial Disclosure	Full Disclosure
Panel A: Experiment 1						
1	3.13	3.13	3.13	0.00	0.00	0.00
2	1.14	1.02	1.26	0.53	0.56	0.50
3	1.04	1.19	0.89	0.63	0.73	0.52
4	0.99	1.13	0.85	0.77	0.71	0.83
5	1.11	1.04	1.17	0.89	0.85	0.93
6	0.71	0.85	0.57	0.71	0.73	0.70
7	0.72	0.69	0.76	0.59	0.52	0.65
8	0.47	0.42	0.52	0.34	0.38	0.30
9	0.49	0.56	0.41	0.54	0.48	0.61
10	0.60	0.69	0.50	0.54	0.52	0.57
Panel B: Experiment 2						
1			2.80			0.00
2			1.27			0.44
3			0.93			0.56
4			0.85			0.59
5			1.13			0.75
6			0.69			0.53
7			0.58			0.48
8			0.46			0.31
9			0.40			0.37
10			0.41			0.40

Appendix

See Table 8.

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