RESEARCH ARTICLE

Market Imitation and Win-Stay Lose-Shift Strategies Emerge as Unintended Patterns in Market Direction Guesses

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Abstract

Decisions made in our everyday lives are based on a wide variety of information so it is generally very difficult to assess what are the strategies that guide us. Stock market provides a rich environment to study how people make decisions since responding to market uncertainty needs a constant update of these strategies. For this purpose, we run a lab-in-the-field experiment where volunteers are given a controlled set of financial information -based on real data from worldwide financial indices- and they are required to guess whether the market price would go "up" or "down" in each situation. From the data collected we explore basic statistical traits, behavioural biases and emerging strategies. In particular, we detect unintended patterns of behavior through consistent actions, which can be interpreted as *Market Imitation* and *Win-Stay Lose-Shift* emerging strategies, with *Market Imitation* being the most dominant. We also observe that these strategies are affected by external factors: the expert advice, the lack of information or an information overload reinforce the use of these intuitive strategies, while the probability to follow them significantly decreases when subjects spends more time to make a decision. The cohort analysis shows that women and children are more prone to use such strategies although their performance is not undermined. Our results are of interest for better handling clients expectations of trading companies, to avoid behavioural anomalies in financial analysts decisions and to improve not only the design of markets but also the trading digital interfaces where information is set down. Strategies and behavioural biases observed can also be translated into new agent based modelling or stochastic price dynamics to better understand financial bubbles or the effects of asymmetric risk perception to price drops.

Introduction

We constantly make decisions that are choices between two alternatives. However, being binary choices does not necessarily imply that decision making follows a simple process since

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the necessary information to make a well-grounded decision might not be easily understood or splitted up into numerous and very diverse pieces. Financial markets are a good example where this type of complex binary decisions have to be quickly done. For instance, imagine you are a trader. You will be then facing the following dilemma everyday: Will the market go up or down? This is the most fundamental question that any financial trader, analyst, advisor, and even non-professional investor with some savings on a given stock is trying to answer using information available from the past -or even from the present. The key point is to anticipate your action at least one step ahead to what the market will finally do and decide to buy or sell accordingly with the hope of getting some profit from each trade.

Stock price movements are triggered by the matched bids and offers listed in the order book [1]. Bachelier already proposed in 1900 a pure random walk through a binomial process in discrete-time form to describe the resulting price dynamics [2]. The French mathematician compared the trader as a gambler and admitted in this way that the speculative markets are driven by an important degree of uncertainty (see for instance [3, 4] for a much more recent contribution analyzing the tension between strategic, or skilled, and random, or gambling, decisions but in the case of the poker game). Later on, *rational theory* and *efficient market hypothesis* better formulated the link between trader's expectations and the evolution of financial prices with the so-called utility function [5, 6]. This robust theory could synthetically be formulated with the following couple of assumptions: (1) information contained in the past is instantly and fully reflected in the current price, and (2) there is no "free-lunch" without taking any risk which technically means that there is an *absence of arbitrage* [1]. The notion of market efficiency brings out a conclusion which appears to be counter-intuitive for a layman: the more efficient the market, the more random is the sequence of price changes, being the most efficient market the one where price changes are completely random and unpredictable [1, 7].

Some studies have found that at least the so-called technical trading strategies are less successful than random strategies [8] and that basic properties in the order book dynamics can be explained by an agent based model which sends to the market buying and selling orders in a complete random way [9]. However, being humans, we still expect to make the correct guess and at least have a better performance than just throwing a coin and this may lead to some behavioural biases [10]. Traders intend to find trends in historical data or hints in any other kind (endogenous and exogenous) of information to reach the inefficiencies of the market which presumably are quickly dissolved in the trading floor [7, 11].

One could keep an eye in some financial indexes such as the Dow Jones or the Japanese Nikkei or one could even consider the opinion of a guru. In each case and even dynamically, a trader dives into the ocean of information available and finds out his own recipes and strategies. Several studies have already detected traces of different information explorations in the financial trading activity [12–20]. Correlations have been found between daily number of mentions of a company in the Financial Times and the daily transaction of that company [13], or have quantified possible warning signs of stock market moves based on activity in *Google* [12, 14] or *Yahoo!* [15, 20] query volumes, *Wikipedia* page views [16], and *Twitter* volume feeds [17]. It is also true that the full amount of information available is neatly impossible to grasp and to analyze in the too limited period of time between transactions. In this sense, it has also been said in the context of human decision making that traders act on the basis of what is been defined as *bounded rationality* [21, 22]. Other economists also introduced the *prospect theory* [23, 24] as an alternative approach to the utility function by considering psychological and framing factors in decision making. Risk perception shifts [25] and judgment under uncertainty biases [26] have been observed in several experiments able to tune the decision frame by for instance changing the formulation of a problem.

The speculative markets with their rules and mechanisms are indeed a perfect scenario for studying human decision-making mechanisms in an uncertain environment. However, it is difficult, yet not impossible, to monitor the behavior of expert traders [11, 27–30], and also traders are a biased sample not representative of the society as a whole. For this reason, we designed a controlled experiment that simplistically emulates a trading screen with data from real financial markets, and we asked a large group of volunteers to respond to the question: Based on the information that you have on your screen, do you think that the market will go up or down? The experiment was repeated under four different control settings, and for each of them the volunteers were asked to respond the same question in 25 consecutive rounds. We tracked how many types of information a participant consulted -and for how long- before each decision was made to obtain quantitative measurements for later analysis.

This type of experiment might be understood as a simplified version of the learning-to-forecast laboratory experiments with human subjects where aggregate price fluctuations and individual forecasting behaviour is studied [31, 32]. This experimental setting also frames decision making within the so-called Stimulus-Response-Outcome (S-R-O) contingencies [33–35] and plays with the intrinsic relations between belief and performance [36, 37]. In each round, the participant firstly can explore the quantitative information available (that is: historical price in different ways that include moving averages at three different time windows, other markets performance, and expert's advice). Secondly, the participant decides whether the given market will go "up" or "down", and thirdly she receives feedback whether her guess was correct or wrong. Using real financial time series from several well-known markets, we introduce an uncertainty which forces a constant update in participants' strategies due to the extreme variability of the market. This kind of situation where participants have to respond with their guesses receives the name of *unexpected uncertainty* or *volatility* [33–35].

Therefore, we present the results of an experiment with a large heterogeneous group of volunteers aimed to obtain general conclusions concerning human decision making. In particular, the experiment was specifically designed to address to the *efficient market hypothesis* and how individuals digest information available [30, 31]. Participants were then solely asked for a binary decision (market "up" or market "down"), which constitutes a simple binomial process allowing us to draw conclusions by means of easy-to-apply and quantify statistical tools. The experimental setup we propose is indeed directly related to the most fashionable financial trading services nowadays. Mobile trading applications, even through Facebook, are quickly growing worldwide, taking the space from more paused and sophisticated electronic trading applications for laptop or desktop computers. Also, similarly to our experimental setup, financial services offered to retail investors are mostly binary options contracts because mobile devices only allow for a limited and quick interaction. Buying or selling binary options through mobile devices is almost comparable to guessing market directions in the way we here explore.

Materials and Methods

The experiment was carried out inside the context of DAU Festival, a board game fair held in Barcelona during the weekend of 14th and 15th of December 2013. The event was organized by the Institute of Culture of the City Council and attracted 6,000 attendants from Barcelona and its surroundings. The experiment is framed inside the Pop-Up Experiment concept described in [38]. Participants did not know in advance the details of the experiment and were asked to play with Mr. Banks (for the participants the experiment was referred as a game) via an interface specifically created and accessible through identical iPads only available in a controlled area -a space with chairs isolated from the rest of the festival. At least three researchers simultaneously supervised the experiment at all times, preventing any interaction among the volunteers and avoiding that anybody was repeating the experiment. In order to satisfy privacy issues, all personal data about the participants was anonymized and de-identified in agreement with the Spanish Law for Personal Data Protection. An online informed consent was given to all participants. Data collected was hosted in a server within the Universitat de Barcelona system, and placed into two different files and directories: one with the player's actions and another with personal data. An id or alias with no reference to personal data was used to link the two databases. Personal data retrieved contained email address, genre, age range and studies. The whole protocol was approved by the institutional review board and data protection commissioner of the Universitat de Barcelona.

The data shown in the game was taken from real historical records of different international markets. In particular, we collected 30 series of 25 consecutive days of stock data picked from the period between 01/02/2006-12/29/2009 of daily prices of: the Spanish IBEX, the German DAX and the S&P500 from United States. The 30 series show different tendencies, specifically 10 with a downwards trend (*bearish* market), 10 with upwards trend (*bullish* market) and 10 with no specific trend at all (*flat* market). Series were assigned randomly to each participant at the beginning of each experiment. Volunteers were told that they were playing with real data but there was no mention about which was the specific market nor about which was the time period of the series to play with.

The main setup of the experiment consisted of a screen that showed the information about the market with two buttons to select if the market would go up or down. As shown in top Fig 1, the information available could be easily consulted with five buttons that allowed easy navigation across the different screens. The first screen (which corresponds to the home screen) contained the price evolution on a daily basis of the series that should be predicted. The screen was not only plotting the series from the first round, but also the previous 30 days from that round. This screen incorporated two extra buttons that showed a 5-day moving average and/or the 30-day moving average. The second screen showed a chart of the intraday price of the day before. The third screen showed an expert that offered advice using the sentence '*Current volatility is high (low) and the price will go "up" ("down")*'. The expert advice on the price change was correct 60% of the times but participants were not aware of this. A fourth screen simplified market evolution with just including arrows in green ("up") and red ("down") from market data of the last 30 days. Finally, a fifth screen included information of 9 other indexes (S&P500, DJI, NASDAQ, FTSE, IBEX, CAC, DAX, NIKKEI, HSI) from 3 different continents with arrows in green ("up") and red ("down") of the last 3 days. Red and green colors were chosen to be consistent with classic colours palette of trading floors infographics (See Figs J-N in S1 File).

The volunteers were asked to guess the price change using this interface 100 times, organized in 4 different scenarios with 25 rounds each. Each guess had a limited time of 30 seconds and, before making a decision, the participant was able to consult the information available according to the scenario constraints. Applying a gamification approach, each participant started the game with 1,000 coins. If the participant made a correct guess, their current number of virtual coins were incremented by 5% while, if she got a wrong guess, she got a negative return of the same size. This gamifcation approach help us to engage the participants into responding the 100 questions of the experiment.

As in a typical experiment in the laboratory, several parameters were tuned in order to know which is the set of conditions of certain phenomena to be produced or what and how it is dependent on. One could easily suspect that time and information are crucial aspects within the making-decision process. In this way, we designed 4 different scenarios in Mr. Banks that could be played by every participant (they were invited to play all scenarios but they could also play just 1 or 2 of them). Participants were randomly assigned to one of the to groups in each scenario once they registered in the experiment. (1) In "Time is money" all information was available but

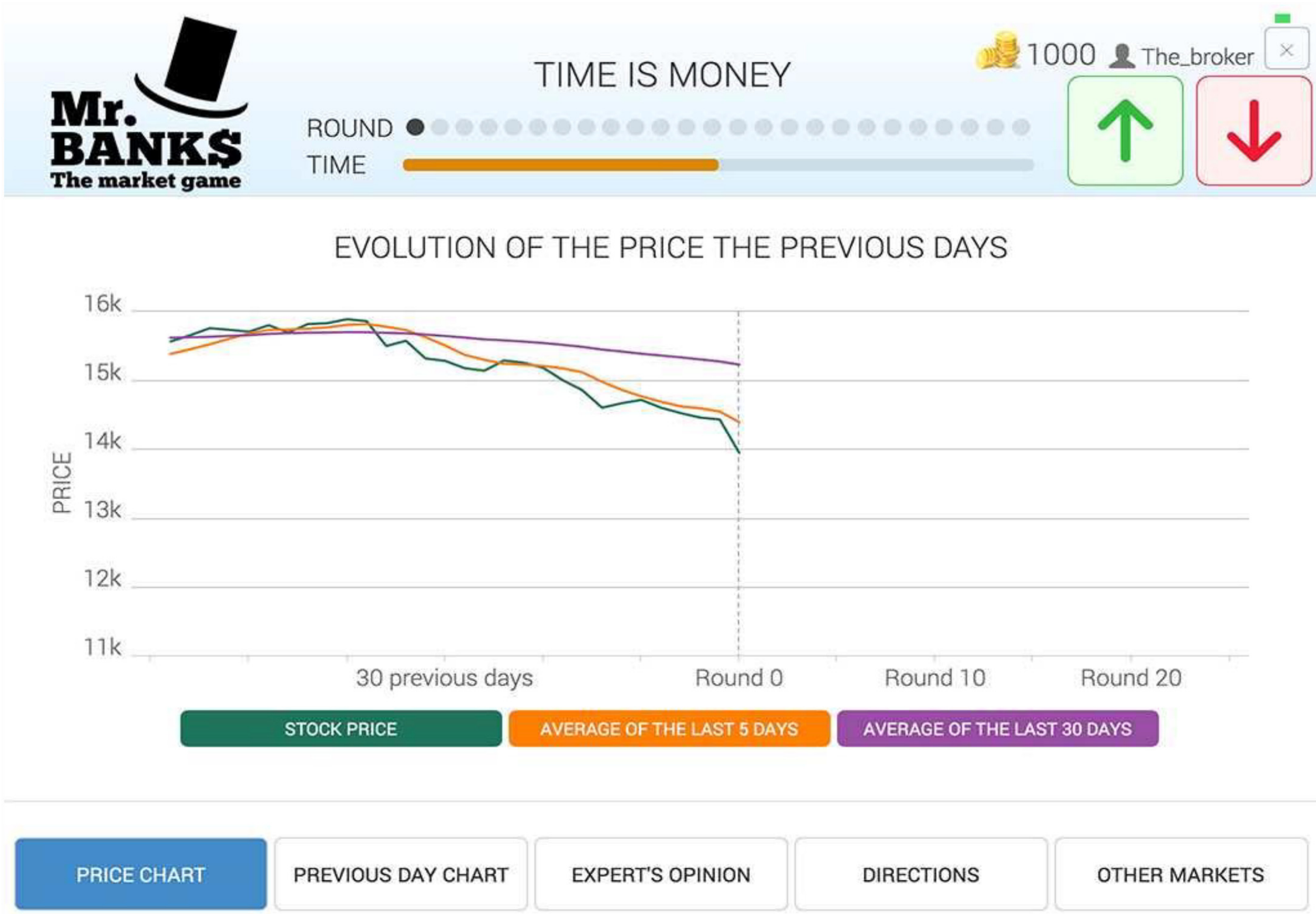

Fig 1. Snapshot of the participant interface. The screenshot shows the home screen with the buttons to select up (green) and down (red). Participants consulted the different types of information available by clicking the buttons placed below the price chart. The top right corner displays the alias of the volunteer and the coins being cumulated during the different rounds. See S1 File for more screenshots of the participant interface.

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50% of the participants had only 10 seconds (group "1I") to make their decision instead of 30 (group "1C"). (2) In "Information is power", 50% of the participants had access to all the information available (group "2I") while the others could only consult the price chart of the home screen without any averages (group "2C"). (3) In "The computer virus", the available information was limited to only one screen apart from the home screen. For one half of the participants (group "3I") this extra information was randomly chosen while for the other half it could be selected (group "3C"). (4) In "The trend hunter" 50% of the participants had access to all the information available (group "2I") and the rest could only see the market directions screen with up and down arrows. They were warned that there was a trend in the financial data without specifying whether it was *bearish* (group "4I"), *bullish* (group "4J") or a *flat* (group "4C") period.

The experiment was also reproduced under the name of "Hack your Brain" during the course of annual event "Collective Awareness Platforms for Sustainability and Social Innovation" (CAPS2015, organized by an FP7 European project) that took place in 7 and 8 July 2015 and was hosted in Brussels (Belgium) (More details in S1 File). A space of 20 square meters at the venue entrance was prepared to carry out the experiment with same protocols and identical interface.

Results

307 volunteers were recruited to participate in the experiment in the DAU Festival of Barcelona. However, after a preliminary analysis we decided to exclude data from the fourth scenario. In this scenario participants were warned that the time series presented a certain trend without specifying which one. The scenario, in this sense, is therefore qualitatively very different from the previous three because it was designed to influence the participant's expectations. Nonetheless, the consideration of such scenarios does not significantly change any of the results presented in this section, as shown in Table E in S1 File.

The pool of participants after filtering the data was finally 283. These participants made 18,436 valid decisions (89 times they ran out of time) and made 44,703 clicks on the screen. The nature of this Pop-Up Experiment allowed us to study a wider variety of demographics [38]. Thus, from the 283 subjects, 99 (35%) were females and 184 (65%) were males. The number of participants by age was distributed as follows: 84 below 15 years old (y.o.), 36 between 16 and 25 y.o., 78 between 26 and 35 y.o., 51 between 36 and 45 y.o., 25 between 46 and 55 y.o., and 9 participants beyond 55 y.o. Additionally they also self-reported about their level of finished studies divided in six groups: None(7), Primary (53), Secondary (37), High School (34), University (148) and Unavailable (4). Participants had no particular expertise in financial markets (only the 22% have ever operated in stock market), only 15% had a high interest in economics and finances and 30% of them believed that they could do it as good as expert traders (see Discussion and survey section in S1 File for further details). Cohort analysis has been carefully discussed in S1 File in order to check possible different performances.

Finally, although we did include different scenarios in our experimental setup (i.e. with different time to decide or information consulted), our analysis found robust behavioural rules across the different settings. For instance, we observed that subjects did not spend the whole available time or information before deciding in most of the cases. Different scenarios might certainly influence behavior in different manners but we decided to focus on those traits which were present in all settings. This coherent behavior can be indeed understood as a way to make results herein presented more robust. The analysis described in S1 File shows that all scenarios reproduce the same patterns in the behavioural traits we present here with no significant differences from the aggregated data.

Time, information and expert advice

Time, information and expert advice are easy-to-quantify magnitudes to characterize the actions of the participants in our experiment. Time spent in each round is distributed around durations much shorter than the 30 seconds available in the experiment. The fastest quartile of the participant's sample makes their own decision in less than 1.614 seconds, half part of participants needs at most 3.431 seconds while the third and slowest quartile of the sample spends more than 6.075 seconds (see top-left Fig 2). Moreover, such values become quite stable after 5 rounds thus indicating a fast and robust learning curve in contrast with immersive and more sophisticated experiences [37]. The average amount (panels) of information being consulted is 2.083 ± 0.011 per round. Besides, time spent linearly grows with an slope of 1.96 ± 0.12 seconds as a function of the number of pieces of information being consulted (see top-right Fig 2).

The experiment was also designed to measure a well-known behavioural bias in financial markets: the influence of the expert advice [10, 39–44]. One of the tabs offered the possibility to consult an expert who was stating whether market will go "up" or "down" in the following step. We somewhat arbitrarily fixed that the expert was telling the truth, and thus guessing right, only 60% of the times. Participants thus trusted their opinion with 0.69 ± 0.03 of probability, which is significantly a higher value (with a 99.87% level of confidence) than the expert

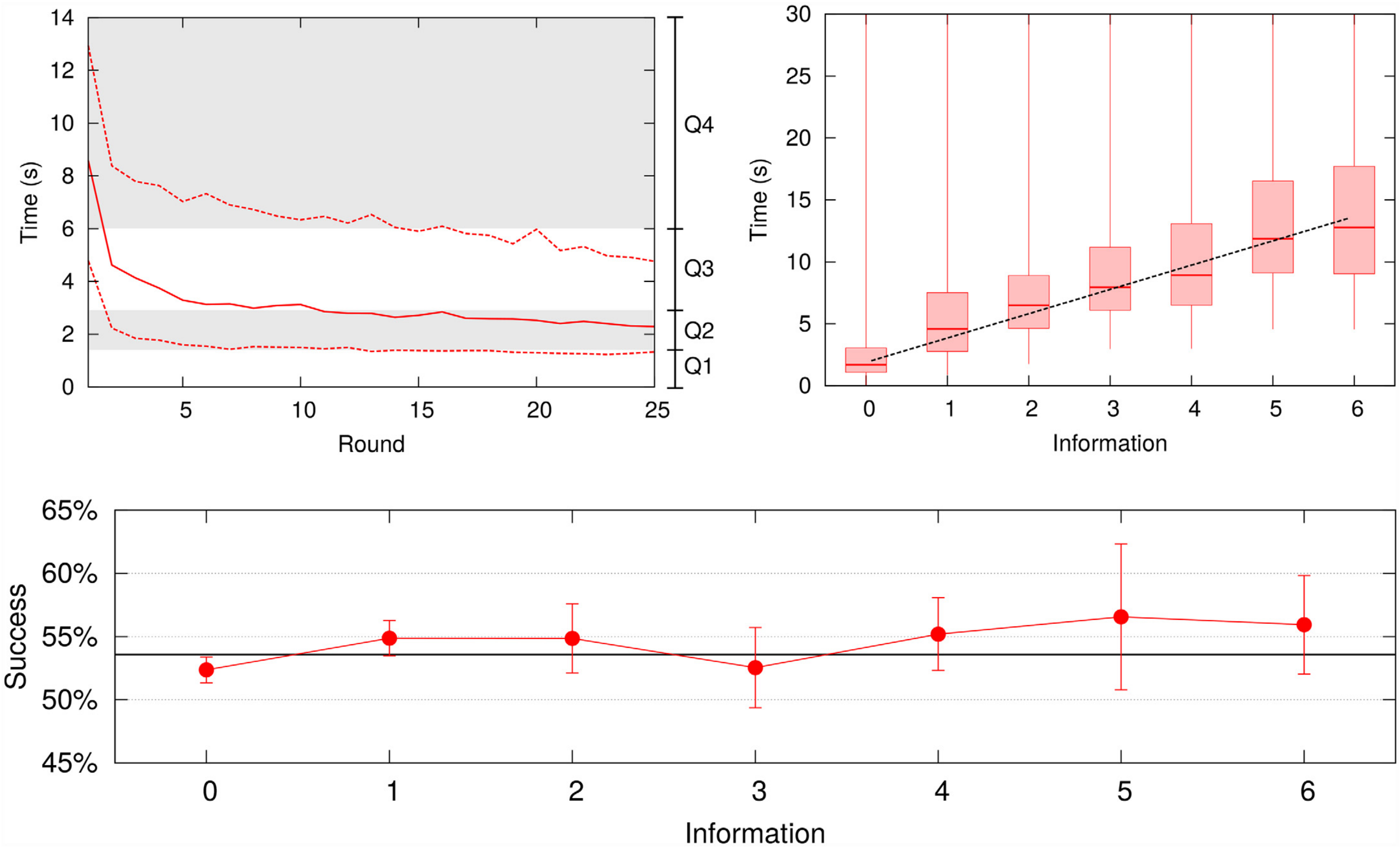

Fig 2. Time, information and performance statistics. (top left) The time spent in each round by participants rapidly decreases as can be seen with the evolution of the median (solid line) and quartiles (dashed). Shadows within the plot also show the different quartile regions when all the 25 rounds are considered ($Q1$ = 1.614, $Q2$ = 3.431, $Q3$ = 6.075). (top right) Boxplot of the time spent to make a decision as a function of the number of additional pieces information being consulted apart from the price chart displayed at the home screen. Plot shows a linear growth with slope 1.96 ± 0.12 and origin ordinate 1.89. (bottom) Success ratio of participants' guesses does not improve when more information is being consulted. Error bars correspond to the Standard Deviation of a binomial distribution.

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forecast reliability. This overreaction phenomena (that can also be understood within the context of the so-called law of small numbers [39]) reinforce the mechanisms on how financial analyst's advice is able to generate abnormal price changes [42]. Similar phenomena is observed in other situations such as the horse racetrack betting tasks [43].

The gender cohort analysis in our experiment shows that men consult significantly more information than women (and consequently spend more time to make a decision) while kids consume much less information than adults (and therefore spend much less time to decide). These findings complement recent results studying the effects of endogenous hormones in trading behaviour [45] and also applies in terms of the educational level of the participants (the higher the level, the more time is spent to make a decision) as there exists a correlation between age and educational level. Table D in S1 File provides further details of the cohort analysis.

Performance, optimistic bias and repetitiveness

Regarding how well participants can anticipate price change, we obtain 9,879 correct guesses in front of 8,557 incorrect guesses, therefore volunteers had a global success empirical probability of 0.536 ± 0.004. This result is slightly above of 50% success ratio that one could expect for a fully random process. One could hypothetize that this higher success ratio is achieved by

Table 1. Behavioural biases with respect to the market dynamics.

	Subjects		Market		Difference	
	Decisions	Probability	Ocurrences	Probability	of probablities	in SD units
"up"	11137	0.606 ± 0.004	10382	0.533 ± 0.004	+0.073	+8.37
"down"	7299	0.394 ± 0.004	8143	0.467 ± 0.004	−0.073	−8.37
"repeat"	9889	0.561 ± 0.004	9445	0.536 ± 0.004	+0.025	+4.77
"change"	7732	0.439 ± 0.004	8176	0.464 ± 0.004	−0.025	−4.77

The first column indicates the decision of a single round "up" or "down", or with respect to the previous one, "repeat" or "change", for either the participants in our experiment (second and third columns) and market data (fourth and fifth). The last to columns compute the difference between humans and market either directly (sixth column) or in terms of Standard Deviation units as defined in the first section of S1 File (seventh column).

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considering all the information provided and using the available time to think about it. However, bottom Fig 2 shows that consulting more screens of information, or spending more time looking at the information, do not improve performance -as has also been observed in other contexts such as sports forecasting [44]. Those participants who played the scenarios where they had information restricted or time shortened (see Materials and Methods) do not show significant differences in their success ratios. Moreover, the fact that success ratio differs in *bullish* markets (0.550 ± 0.011), *flat* markets (0.533 ± 0.011) and *bearish* markets (0.503 ± 0.011), lead to think that participants may have a sophisticated behavioural bias behind. The cohort analysis does not show significant differences of success in terms of gender and age although, as mentioned above, there are differences in terms of the time spent to make a decision and the amount of information being consulted.

Table 1 shows that the probability that participants choose "up" ($p(\uparrow) = 0.606 \pm 0.004$) is not only very far from a pure random value (0.5) but also significantly higher than the empirical probability of the market to go "up" ($p(\uparrow_M) = 0.533 \pm 0.004$). Such optimistic bias is also well-known in behavioural finance literature [46] and our experiment allows to make this effect neatly evident. The bias is general among all cohorts studied; age, genre and education level (see Table A in S1 File).

It is also known that humans tend to repeat same decision [10]. Table 1 shows that this tendency in our experiment has a probability of 0.561 ± 0.004. The value is significantly higher than the 0.5 from a random behaviour. One could argue that participants believe that market has a trend so they act accordingly. However, such probability is significantly higher than the probability that the market repeats the same outcome (0.536 ± 0.004) so this behavioural traits can be interpreted as another bias since it relies on a belief perseverance (also called confirmatory bias) [10]. The cohort analysis summarized in Table B in S1 File only shows a single exception: the well known fact that children are more inconstant in their decisions [47].

Market Imitation and Win-Stay Lose-Shift emerging strategies

Our minds have a tendency to introduce biases in processing certain kinds of information. Furthermore, they also create unintended patterns through consistent actions, that is: emerging strategies [35, 48]. The *Market Imitation* (MI), also called *automatic imitation* by neuropsychologists [49], is one possible emerging strategy since it is an effective way of saving time and attention effort in decision making. It is indeed a common product of bounded rationality [21] based on an stimulus response which does not wait for an outcome and just mimics the external input received. This strategy is present in many economic contexts (for instance: corporate strategies, domestic economy or householding economy) and is playing a role within innovation and creative processes as a risk aversion attitude, as a routine behaviour, as a reciprocity action or as a competitor matching. In our case, to follow the MI strategy means that participant copies market movement direction of the previous round. That is: if the market went "up" ("down"), participant chooses "up" ("down"). The MI strategy has been carefully studied for instance in rock-paper-scissors game [50] and in generation of random sequence by individuals [51].

The S-R-O design of our experiment [33] also allows us to study whether the performance in previous round ("correct" or "wrong" guess) affects participant's decisions. In this sense, another possible emerging strategy is the *Win-Stay Lose-Shift* (W-S L-S) that relies on an stimulus response which, in contrast with the MI strategy, considers the outcome of the previous action. In this case, participants repeat their last decision when this was correct, and change the decision when it was a wrong guess. This Win-Stays Lose-Shift pattern has also been found in several contexts [52–54] where appears to be a quite common heuristic learning strategy. The strategy has been studied from diverse perspectives such as game theory, machine learning, and psychology. It is said that it was firstly investigated within field of statistics as an improvement over randomization in bandit problems [55].

To quantify the importance of these two emerging strategies in our experiment, we have computed the mutual information [56] (that is: mutual dependence) to measure the influence of the two different emerging strategies in the participant's actions. Mutual information is defined as

$$I(X, Y) = \sum_{x,y} p(x, y) \log \frac{p(x, y)}{p(x)p(y)} = \sum_{x,y} p(y|x)p(x) \log \frac{p(y|x)}{p(y)}, \quad (1)$$

where X and Y are the two random variables. It is defined positive and takes values between 0 and 1, meaning that both random variables are completely independent or that they are perfectly correlated respectively. Mutual information values are given in bits units since we have used the logarithm with base two.

Firstly, in relation to the MI strategy, we compute the mutual information between participant decision series ("up" and "down") and previous market movements ("up" or "down"): 0.045 ± 0.010 bits. And, secondly in relation to the W-S L-S strategy, we compute the mutual information between participant decision series ("up" or "down") and outcome of previous action ("correct" and "wrong"): 0.050 ± 0.010 bits. In both cases, mutual information might seem quite small but it is significantly higher than not only the market self-information case (that is: the mutual information between the series of direction of market changes shifted one day, 0.003 ± 0.010 bits) but also the participant's self-reflected actions case (that is: the mutual information between the guesses series shifted one step, 0.005 ± 0.010 bits). S1 File has a specific section discussing all these results.

Indeed, we can go one step further by looking at the conditional probabilities related to these two emerging strategies. Fig 3 confirms the presence of the MI strategy in our experiment and shows a striking difference between the empirical probability to choose "up" after market having raised ($p(\uparrow | \uparrow_M) = 0.714 \pm 0.005$), and the probability to do so but after market having fallen ($p(\uparrow | \downarrow_M) = 0.469 \pm 0.006$). These two conditional probabilities differ from the unconditional probability to choose "up" ($p(\uparrow) = 0.606 \pm 0.004$) by 18.59 Standard Deviation (SD) units above and 19.04 SD units below respectively. The imitation is also relevant in the "down" case. The probability of choosing "down" conditioned to the market went "down" is $p(\downarrow | \downarrow_M) = 0.531 \pm 0.006$ being 20.37 SD units above the unconditional probability $p(\downarrow) = 0.394 \pm 0.004$ from Table 1, while $p(\downarrow | \uparrow_M) = 0.286 \pm 0.005$ is 16.86 SD units below this value. It is worth mentioning that the MI strategy describes a behavioural bias towards upwards market direction that might be linked to optimistic behaviour and overconfident position with respect positive trends in financial markets [46] and even linked to financial bubbles [22, 57].

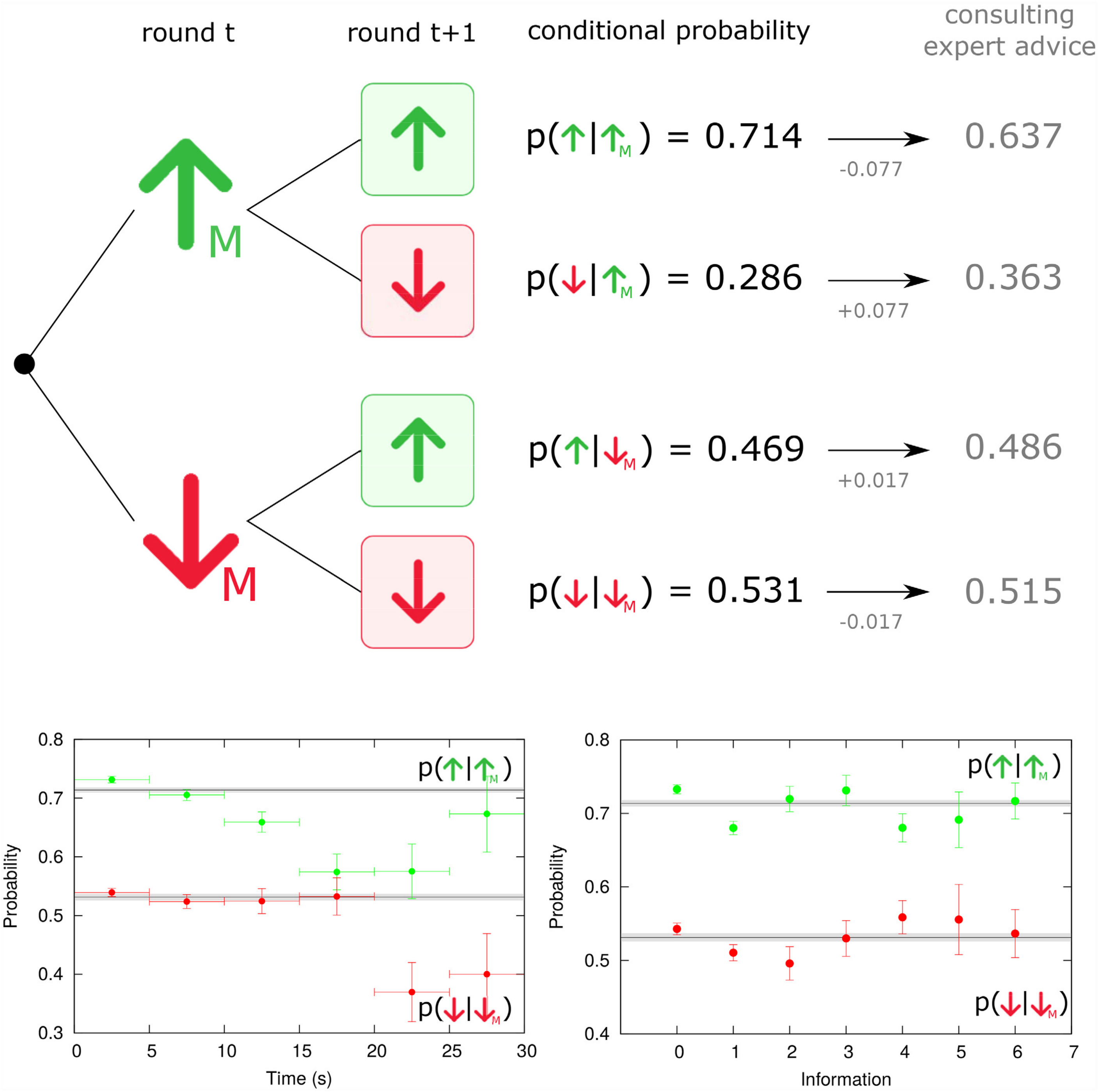

Fig 3. Decision conditioned to market: the Market Imitation emerging strategy. Empirical conditional probabilities of guessing whether market will go up or down are positively correlated with market behavior in the previous round. Participants tend to mimic market movement and this behavior is specially important when market went up ($p(\uparrow \mid \uparrow_M) = 0.714 \pm 0.005$). The effect is however sensitively diminished when subject consults expert's advice (0.637). (down left) The time spent to make a decision plays a significant role when a participant guesses that market will go "up" (green) in contrast with case when a participant guesses that market will go "down" (red). (down right) Checking an additional type of information also tends to diminish conditional probabilities but when a participant consults more information, the participant mimics market movement again. Horizontal lines in bottom plots provide aggregated results and shadows their error bars. Error bars represent the Standard Deviation of a binomial distribution.

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Fig 4 focuses on the W-S L-S strategy. In this case, the probability to repeat a successful decision is 0.682, that is 0.121 (19.92 SD units) higher than the probability to repeat any decision, 0.561 as shown in the Table 1. In the same way, the probability to change a wrong decision is 0.579, what is 0.140 (21.18 SD units) greater than the probability to change any decision. Again we observe a behavioural bias being more probable to persist after a successful guess than to change decision after a wrong guess. In this case, shifting the strategy when guess is "wrong" can be also related to negative skewness risk [58], to the asymmetric risk (and the increment of market volatility) due to unexpected price drops [59, 60].

One obvious question we can formulate is which is the dominant emerging strategy in our experiment. One way to measure the possible differences is by computing the conditional mutual information (see S1 File for the whole analysis). Mutual information between participant's actions and previous market movements conditioned to the previous outcome is 0.05 ± 0.04 bits, while mutual information between participant's actions and previous outcome conditioned to the previous action market movements 0.07 ± 0.04 bits. These two conditional information values are telling us that there is non-redundant information. However, market direction (and its subsequent MI strategy) seem to be more relevant since the mutual information conditioned to know the market is higher.

Another possible approach to evaluate the dominant emerging strategy is the one summarized in Fig 5. In this figure we unfold all possible scenarios with a two-step chain where the MI and W-S L-S strategies appear and can be therefore compared. Thus, for instance, the "up-success-up" probability is 0.729 while the probability related to the MI strategy (only conditioned to what market did before, without considering the performance) is 0.714, thus being much closer than the probability (0.682) related to the W-S L-S strategy. Fig 5 shows how MI is systematically closer to the two-step conditional probabilities than the W-S L-S strategy. Therefore, the analysis suggests that the impact of MI strategy is greater than that of the W-S L-S strategy and reinforces the conditional mutual information results.

Emerging strategies versus information, time and expert advice

We test if the conditional probabilities of the MI strategy are also influenced by other variables like the time used to make a decision, the amount of information examined or if the participant consulted the expert's advice. As it can be observed in bottom-left of Fig 3, generally the more time spent to make a decision the lower the values of $p(\uparrow \mid \uparrow_M)$ and $p(\downarrow \mid \downarrow_M)$ with respect to the reference value. Such probabilities are however above the reference value when the decision is made without consulting any information and fall below the reference when one extra panel is consulted (bottom-right Fig 3). The expert's advice also affects the values of $p(\uparrow \mid \uparrow_M)$ and $p(\downarrow \mid \downarrow_M)$ by reducing in 0.077 and 0.017 respectively. W-S L-S strategy is also susceptible to either time, amount of information and expert advice influences in a similar manner. Regarding the expert's advice, the probability to repeat after a success having consulted the expert is reduced by 0.072 (−6.80 SD units) with respect to the reference level, while the case to chose "down" when market has fallen and having consulted the expert is 0.037 (−2.92 SD units) below the reference.

We next perform a coarse-grained approach where we tag all the participant's decisions using the two possible labels: if they "Follow (emerging) Strategy" or if they do "Not Follow (emerging) Strategy". Thus, "Follow an Strategy" in the MI case would mean to choose "up" after market goes up, and choosing "down" after market goes down (see Fig 3). The values of the other two branches in the tree diagram of Fig 3 would be aggregated to conform the "Not Follow Strategy" probability. We can proceed in the same way with W-S L-S, where "repeat" after success or "change" after a wrong guess would mean "Follow Strategy". Interestingly, we

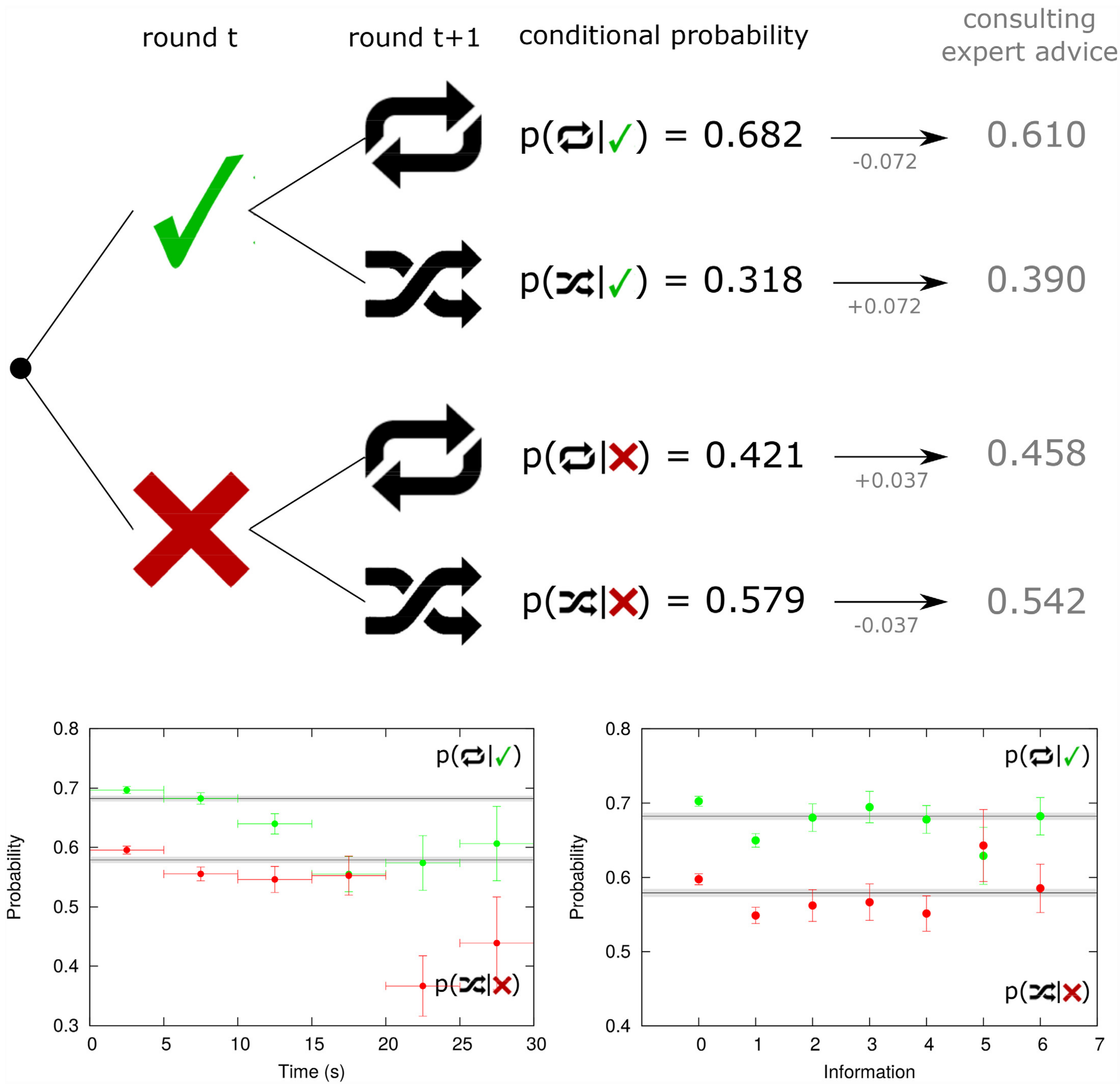

Fig 4. Decision conditioned to performance: the Win-Stay Lose-Shift emerging strategy. Empirical conditional probabilities of repeating previous guess are positively correlated with success and failure of the previous guess. The highest probability corresponds to repeating the previous guess when this was correct (0.682). The expert's advice partially neutralizes the effect (0.610). (down left) The conditional probability decreases when participants spend more time to make the decision in both cases: being "correct" (green) and being "wrong" (red) in the previous round. (down right) The conditional probability initially diminishes but when a participant consults more information it oscillates around the mean in both cases: being "correct" (green) and being "wrong" (red) in the previous round. Horizontal lines in bottom plots provide aggregated results and shadows their error bars. Error bars represent the Standard Deviation of a binomial distribution.

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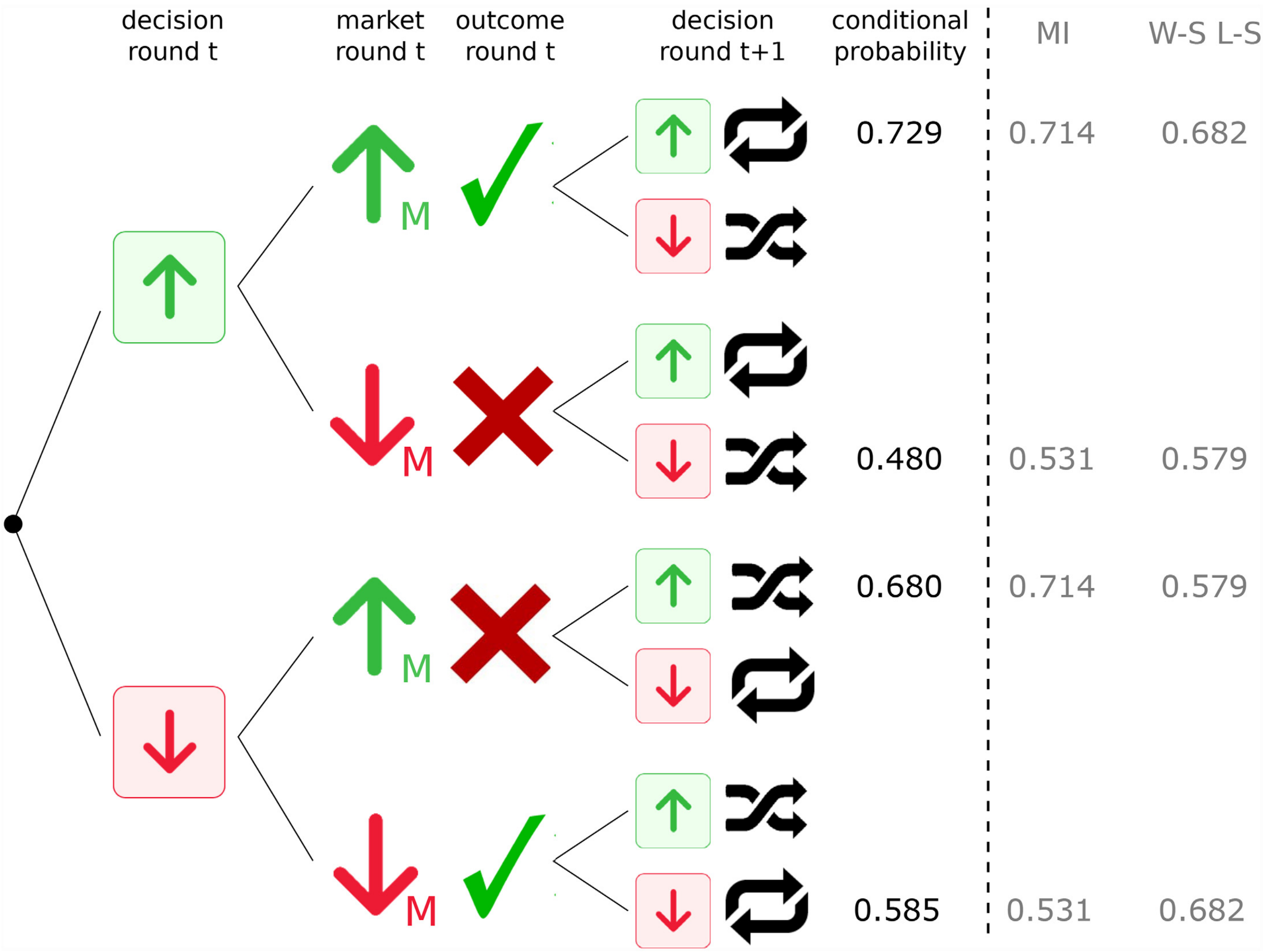

Fig 5. Two-step Markov chain to observe that Market Imitation is the dominant emerging strategy. The tree of possibilities for the probability to choose "up" or "down" depending on two conditions: the direction of the market in the previous round and the performance of the volunteer (success or not) in the previous round. The tree includes the conditional probabilities of the Market Imitation and Win-Stay Lose-Shift emerging strategies to observe which of them is the dominant strategy. We observe that Market Imitation conditional probabilities are closer to the aggregated conditional probabilities corresponding to the event to "Follow and Strategy" than those from the Win-Stay Lose-Shift emerging strategy.

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show in S1 File that for our binomial scheme the aggregation process for the conditional probabilities of the MI and W-S L-S strategies lead to the same events for "Follow Strategy" and "Not Follow Strategy".

The probability to follow any of the two emerging strategies is 0.634 ± 0.004, that is 0.134 (25.70 SD units) over the 0.5 reference if decisions were random. The probability to "Follow Strategy" is also affected by time, information and expert's advice as shown in Fig 6, but now the influence seems more evident than in the cases where the two strategies are treated separately. It is very clear that the tendency to follow any strategy decays with the time spent to make a decision. Moreover, participants without extra information are going to follow much more the emerging strategies in clear contrast to the case with just one extra piece of information (center Fig 6). Surprisingly, more information does not motivate participants to abandon these intuitive strategies since, after consulting more than 1 panel, the probability to follow the

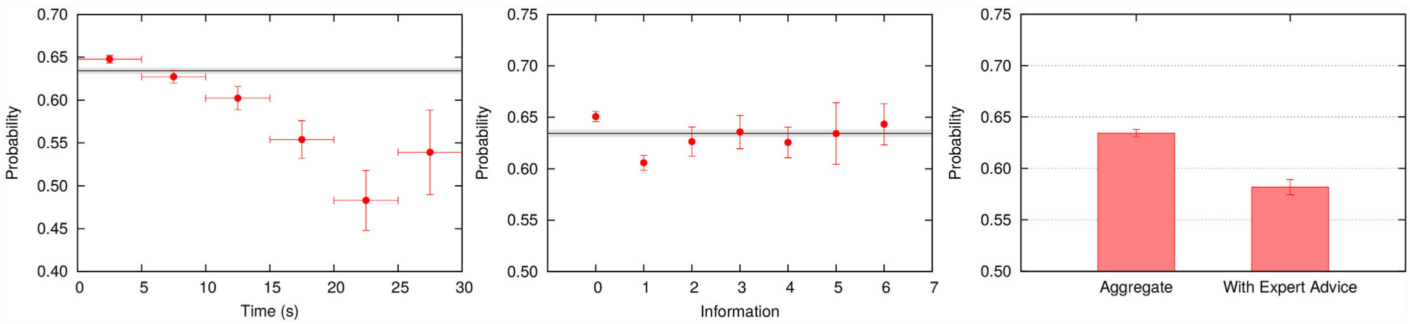

Fig 6. Aggregated strategies: time, information and expert advice dependences. (Left) The probability to follow any of the described strategies depending on the time spent to make the decision. The range between 0 to 30 seconds has been divided in bins of 5 seconds. (Center) The probability to follow any of the described strategies depending on the number of different information panels consulted. (Right) The bar on the left accounts for the probability to follow any of the described strategies, whereas the bar on the right indicates the same, but conditioned to having clicked on the expert's advice panel. Solid black line denotes the total probability while the limit of the shaded area and the error bars denote the Standard Deviation.

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strategy increases and stays quite stable close to the same value as to the case of having not consulted extra-information. One possible explanation for this is that two or more different pieces of information are also two different kind of stimulus and they may induce to two different responses (perhaps contradictory responses). Due to an information *overload* [30], actions would be mostly again governed by emerging strategies. The influence of the expert's advice then becomes very evident in the right panel of Fig 6. We observe that the probability to follow any strategy after the expert is consulted is 0.582, which is 0.053 below the reference value (6.47 SD units).

Indeed, the simplicity of the coarse-grain analysis make possible to perform a cohort analysis. Table H in S1 File shows that all cohort groups tend to follow these intuitive strategies with a probability between 0.6 and 0.7, thus providing more universality in this finding. Finally, we can go even deeper in this issue in two specific cases. Firstly, we have observed that women tend to decide faster than men, which is probably related with the fact that women follow with a higher intensity intuitive strategies than men. This feature, which can be linked to a more efficient decision-making process, do not undermine their success ratio in their guesses. Secondly, as we have discussed, children from 0 to 15 years old are the fastest age group by far in taking decisions. However, the differences are not that relevant as those observed among men and women when we look at the probability to follow the intuitive strategies. This feature can, in this particular case, be attributed to a more volatile or hectic behaviour in kids as it has been previously suggested in the context of the social dilemmas [47]. This explanation is supported by the fact that this age group has the lowest probability to repeat previous guess. See cohort analysis section in S1 File for further details.

Discussion

Facing environments with high levels of uncertainty is a very complicated task for human beings [22]. We have serious difficulties when dealing with randomness, we tend to see patterns when there no exist at all [48]. Moreover, decision-making process involves multiple factors, which may be far from a rational behavior, like stress and panic. Therefore, models that only depart from *rationality* and *self-interest* could also incorporate concepts linked to how humans cope with uncertain environments [10].

In this experiment, carried out inside the Pop-Up Experiments framework [38], we put a group of volunteers non-expert in finance under such uncertain environment. We asked participants to predict the day-by-day evolution of a series of real historic prices of a certain index, allowing them to consult some information while registering every action [22, 31]. The 18,436 decisions made by 283 subjects are very far from being random. As shown in S1 File, subjects were generally not experts while 47% found that information was useful for making decisions. In terms of which information was most relevant to them there is no consensus at all while, when asked how did they make their decisions 47% of the volunteers admitted that intuition was more prominent than financial information. Additionally, when asked if they think they could predict the market having same information as experts, 49% of participants said "no" after doing the experiment (30% before the experiment).

Looking directly at the data from their selections, we find two behavioral biases through the repetition of consistent actions: a preference to guess that the market will move in the same direction as the previous day and a tendency to repeat the previous decisions when they are correct. We identify *Market Imitation* and *Win-Stay Lose-Shift* strategies as the mechanisms responsible of such biases. These strategies also appear in other contexts [51, 54]. The coarse-grain approach allows us to identify these strategies as something intuitive because of three reasons: (1) the less time used to make a decision the more likely to follow any of this strategies, (2) the probability to follow any strategy is significantly higher when only a price chart has been consulted and (3) consulting the expert (as a clear exogenous signal) significantly mitigates the likelihood to follow this strategies. The wide range of demographics in our sample also allows us to identify that women and children are faster in taking decisions than the rest. However, this is reflected in their actions in a different manner. Women are then more prone to follow intuitive strategies than men while kids are the less persistent age group in their actions. Moreover, we repeated the same experiment in a conference with different demographics and we confirmed the robustness of our findings. We have also looked at the influence of the previous two steps and we find that, although mutual information values are not relevant anymore, one can still find some traces of behavioural biases. See S1 File for further details on these two last results.

The direct implications of this study point to market policy, traders and market modelling. The pretended advantages of the vertiginous pace of markets and particularly the high-frequency trading are nowadays questioned [61]. In the scale of non-expert individuals, who sometimes might decide to manage their own portfolio, we have seen that fast and uniformed decisions tend to intuitive and pre-established behaviors in contrast with rational and deliberated decisions. However, it should be investigated whether such intuitive behaviours take place also in real markets but there are already studies finding some evidences in traders and fund managers behaviors [22, 30]. Our findings anyway supports the idea of decelerating the vertiginous velocity of markets in order to gain rationality and information filtering. From another perspective, our results are of interest for better handling clients expectations of trading companies, avoiding behavioural anomalies in financial analysts decisions and improving the trading digital interfaces where information is set down. It should finally carefully be analyzed the information provided and how it is hierarchized to improve market in many senses [30]. In a more general way, our results could also help to develop new agent based modelling or stochastic price dynamics to better understand financial bubbles or the effects of asymmetric risk perception to price drops [22, 32, 59, 60, 62]. The study of the different behavioural biases arising form the emerging strategies can provide some explanation of financial bubbles (Market Imitation, specially for the upwards trends) and how price drops increase market volatility (Win-Stay Lose-Shift, when changing previous decision after a "wrong" and thus increment market uncertainty). Individuals, as agents who make decisions living in a society impregnated of contingencies impossible to evaluate and constantly updated where we have to make uninformed decisions, must be aware of these intuitive strategies as a fallacies to avoid or lighthouses that help us to sail in the middle of an ocean of uncertainty.

Supporting Information

S1 File. Supporting information file. In the S1 File (PDF) we present further details about the experiment, statistical tests and additional information.
(PDF)

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Author Contributions

Conceived and designed the experiments: MGR JD JP.

Performed the experiments: MGR JP JD.

Analyzed the data: MGR CS.

Wrote the paper: MGR CS JD JP.

Wrote the software interface for the experiment: JD.

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