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Gazing through the bubble: an experimental investigation into financial risk-taking using eye-tracking

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Abstract

Eye tracking can facilitate understanding irrational decision-making in contexts such as financial risk-taking. For this purpose, we develop an experimental framework in which participants trade a risky asset in a simulated bubble market to maximize individual returns while their eye movements are recorded. Returns are sensitive to eye movement dynamics, depending on the presented visual stimuli. Using eye-tracking data, we investigated the effects of arousal, attention, and disengagement on individual payoffs using linear and nonlinear approaches. By estimating a nonlinear model using attention as a threshold variable, our results suggest that arousal positively influences trading returns, but its effect becomes smaller when attention exceeds a certain threshold, whereas disengagement has a higher negative impact on reduced attention levels and becomes almost irrelevant when attention increases. Hence, we provide a neurobehavioral metric as a function of attention that predicts financial gains in boom-and-bust scenarios. This study serves as a proof-of-concept for developing future psychometric measures to enhance decision-making.

Keywords: Financial bubble, Experiment, Risk-taking, Eye-tracking, Attention, Arousal

JEL Classification: G10, G40, G41, D87, D91

Introduction

Financial investing and risk-taking are topics for which eye-tracking can shed new light on individual- and group-level choices (Ert et al. 2021). Financial decision-making has important implications for both individual and societal welfare and is intrinsically connected to risk-taking, regardless of whether such choices are related to stock trading, capital allocation, or short-term consumption versus long-term savings. It is complex as it implies striking a balance between risk and return over time, mandating high levels of cognitive engagement.

In allocating capital over time, several peculiarities capturing market participants' inconsistent and irrational behavior have been identified, which drive financial decision-making away from the efficient market hypothesis (Fama 1970). Cognitive biases and emotions lead to faulty decisions, which can lead to negative market repercussions. For example, cumulative decisions on the stock market, driven in part by cognitive biases such as overconfidence (Camerer 1989), can cause asset bubbles, which are defined as over-inflated representations of a stock's price above its fundamental value and self-fulfilling price escalations above a predefined intrinsic value (Abreu and Brunnermeier 2003). Such phenomena have caused disruptions and turmoil in financial markets, mainly because of contagion effects or interlinkages with the real economy. In the past few decades, the dot-com bubble burst in the early 2000s, and the subprime bubble in 2008 caused a persistent output decline, leading to increased unemployment. Even though emphasis has been placed on studying equity market bubbles, such phenomena can arise in other markets with similar negative effects, starting from the first historically recorded bubble episodes, the Tulip Fever in the seventeenth century, to recent crypto-asset rallies (Li et al. 2021; Agosto and Cafferata 2020).

More recently, neuroeconomics, a field encompassing tools from cognitive neuroscience, experimental psychology, and economics, has been shown to provide more in-depth information about individual risk-taking that can generate such phenomena compared with standard econometric methods. Investing in the stock market generates emotional reactions triggered by uncertainty and excitement, such as arousal or attention, which can be indirectly measured using eye movements. For example, diminished attention and increased arousal could lead to lower returns, but this can also depend on (1) various socio-demographics such as age or experience investing in the market, (2) behavioral factors such as overconfidence, and (3) period of the market: bubble or bear markets. However, the link between individual investing performance and eye-tracking variables has not yet been thoroughly investigated in this context. Leveraging biometric indicators such as eye movements as proxies for psychophysiological states to predict individual gains can set the stage for their future usage in actual trading contexts and optimal decision-making in similar engaging tasks.

Consequently, we address the following research question: How do eye-tracking biometric indicators influence and predict individual payoffs in a boom-and-bust scenario? We hope that the answers to this question will enrich readers' knowledge and provide, at the same time, the basis for future developments of passive brain-computer interface systems where eye-tracking technology can be used to optimize financial decision-making.

The remainder of the paper proceeds as follows: "Literature review" section offers a brief overview of the literature in the eye-tracking field connected to financial decision-making; "Materials and methods" section describes the experimental design and provides details on the analysis methodology; "Results" section reports the estimation results; and "Discussion" section provides the discussion, limitations of the study, and directions for future research. "Conclusions" section presents the main conclusions of the study.

Literature review

Eye tracking is an established method that offers insights into ongoing cognitive processes and can be considered a versatile application in various behavioral studies (Wedel 2013; Valtakari et al. 2021), including economics experiments (Fiedler and Glöckner 2012; Lahey and Oxley 2016; Sickmann and Le 2016). It has been used to evaluate arousal (Bradley et al. 2008), decision-making in coordination games (Wang et al. 2010; Li and Camerer 2019), and attention (Orquin and Mueller Loose 2013), including preceding shifts of attention in risky decision-making (Franco-Watkins and Johnson 2011a, b).

Traders must process significant volumes of complex information that mandate them to maintain sharp levels of attention to maximize returns for the given risks. Attention is restricted because investors can only process a certain amount of information, given their limited cognitive capacities, and consequently is considered a crucial decision-making variable (Hirshleifer et al. 2011; Tymula and Glimcher 2016). Thus, monitoring biometric indicators for attention, mental effort, arousal, and other physiological measures of stress (von Helversen and Rieskamp 2020) can be beneficial for understanding financial risk-taking.

A strand of literature has investigated the link between risk-taking and eye tracking. For example, Franco-Watkins and Johnson (2011a, b) applied a decision-moving window method to a risky choice paradigm and provided insights into the dynamics of risky decision-making, an example being steady increases in pupillary responses towards the end of the decision-making window. Similarly, Fiedler and Glöckner (2012) investigated the dynamics of risk-taking using eye tracking and found that attention to the outcome of a gamble increases directly with probability and value while attention shifts toward the favored gamble, indicating a gaze cascade effect. Frydman and Mormann (2016) determined that attention to upsides of risky lotteries is correlated with the probability of taking risks. Most notably, they explained a positive causal impact of attention on risky choices. Harrison and Swarthout (2019) developed a model of risky decision-making and found that eye movements affect probability weighting behavior; people who spend more time looking at probabilities tend to decide using expected utility theory.

While the causal impacts of eye tracking and financial payoffs have not yet been explored, several studies have investigated the relationship between eye tracking and financial investments.

In the first study looking into the effects of eye-tracking in investment decisions, Shavit et al. (2010) noted that investors spend more time investigating the performance of winning assets than losing ones. Thus, it is likely that subjects were not only engaged in judgment when investigating their portfolios but may also have been inclined to search for reassuring elements. Similarly, Hüsser and Wirth (2016) measured eye movements to estimate the attention of subjects and confirmed that investors track past mutual fund performance while also being subject to the hot hand fallacy, regardless of disclaimers mandated by regulatory bodies. In addition, Rubaltelli et al. (2016) found that larger pupil dilation is associated with investments in funds, regardless of past performance. Presentation of information on the screen is also important in financial decision-making tasks. Ognjanovic et al. (2019) showed that cluttered screens negatively impact novices more than experts in terms of performance and visual attention measures. More recently, machine learning algorithms trained on eye-tracking data have suggested that decision weights derived from visual salience are associated with investments in stock market experiments (Bose et al. 2020). Gödker and Lukas (2021) experimentally investigated the impact of extreme stock returns on investors' purchasing behavior and highlighted the asymmetric effect exhibited by extreme returns on investors' visual attention, leading to errors when deciding to buy a stock.

Behavior is also influenced by the type of information provided, not necessarily only by where the subjects look at the screen. For example, Hinvest et al. (2018) addressed the conflict between investment and social preferences and determined that it was possible to nudge and classify investors using images related to social behavior and negative social images, eliciting a stronger effect than positive ones. Król and Król (2019a) found that the initial positive information shown to subjects in a stock trading experiment facilitates the elaboration of further positive information; this effect is not present for negative information. As such, positive information has a stronger effect on participants' decisions. In a follow-up experiment using eye-tracking of the disposition effect in a stock-trading task, Król and Król (2019c) found that investigating the process by which a person reaches a decision can more accurately predict how that person will perform in the future.

A recent comprehensive review of attention in decision-making using eye tracking was performed by (Borozan et al. 2022). According to this recent review, no studies have investigated the link between stock trading performance during a boom-and-bust market, confirming the innovative approach of this study. The relationship between eye-tracking variables and individual gains in such a scenario is important, considering the recurrence of bubble episodes in financial markets throughout the years, which will most likely continue to persist. Hence, this study investigated the cognitive processes involved in decision-making during a bubble using eye tracking.

We hypothesized that physiological states generated during trading in a stock market could reduce attention and increase arousal or disengagement, as measured by eye movements. Towards this end, we measured several variables using eye-tracking indicators: pupil dilation as a proxy for arousal, distance from the center of the area of interest (AOI) as a proxy for attention, and distance between consecutive gaze fixation points as a proxy for disengagement. Increased pupil dilation is suggestive of increased arousal, a higher average distance from the center of the AOI indicates reduced attention, and a higher average distance between consecutive gaze points indicates higher disengagement from trading.

Consequently, we address the following research question: How do eye-tracking variables influence and predict individual payoffs in a boom-and-bust scenario? We believe that the answer to this question will enrich readers' knowledge and provide, at the same time, the basis for future developments of passive brain-computer interface systems where eye-tracking technology can be used to optimize financial decision-making. Our findings are novel, as they offer an original perspective on how trading performance correlates with physiological responses as measured by eye movements during the boom and bust of a bubble.

The remainder of the paper proceeds as follows: "Literature review" section describes the experimental design and provides details on the analysis methodology; "Materials and methods" section reports the estimation results; and "Results" section provides the discussion, limitations of the study, and directions for future research. "Discussion" section presents the main conclusions of the study.

Materials and methods

Participants

Twenty-eight healthy subjects with normal or corrected-to-normal eyesight (10 women, mean age 26, SD 3) participated in the experiment in May and June 2017 in a noise-isolated room in Bucharest, Romania. The subjects were graduates of Economics and Finance or were studying for their master's degree in the same major (mean number of years of study = 5, SD = 2), with some participants having industry experience in the financial field (mean = 1 year, SD = 2 years). Several subjects also had trading experience. The experiment consisted of two trading rounds to observe how eye-tracking dynamics change between sessions and whether learning occurs. Because of eye-tracker sensitivity to head motions, data collected from two subjects contained artifacts that rendered it unusable. The final sample consisted of 27 subjects (9 women) in the first round and 26 subjects in the second round (9 women). Subjects gained an average of 1.935 in experimental cash, equivalent to a final real gain of 10 EUR (roughly 4% of the minimum monthly income for 2017) paid in local currency at the exchange rate.

Experimental design

The subjects traded in a simulated experimental market during the two trading rounds. Each subject performed the experiment individually on a computer screen without any interaction among the participants. Each round consists of 30 trading periods, each lasting for a maximum of 30 s and divided into four sub-periods. The subperiods provide information on (in the following order):

1. The current subjects' holdings in cash, stock value, and a figure depicting real-time stock price dynamics.
2. The current period price of the stock and three buttons corresponding to buying, selling, or holding one unit of stock.
3. Previous decisions made by the participant.
4. Earnings in terms of dividends and interests.

The experiment is represented in Fig. 1, where each window is numbered according to its order. The subjects can see the entire figure for the stock market price being updated, not only the last price change.

Each subject received six units of the risky asset (STOCK) and 100 CASH units at the beginning of the experiment. Subjects could trade one unit of STOCK during each period in the CASH units. When a subject buys STOCK, the price accepted to pay is deducted from the amount of CASH remaining during that period. When the subject decides to sell, the amount of money earned from the sale of the asset is added to CASH. In each period, the stock generates either a large or small dividend of {1; 0.40} CASH units for each stock with equal probability and is the same for all subjects for each period. The autocorrelation of the dividend series was set to zero. The endowments, dividend structures, and stimuli were the same for all the subjects.

Holding cash brings a fixed income of 5% interest in each period. At the end of the 30 trading periods, each share is liquidated at 14 cash units, irrespective of the

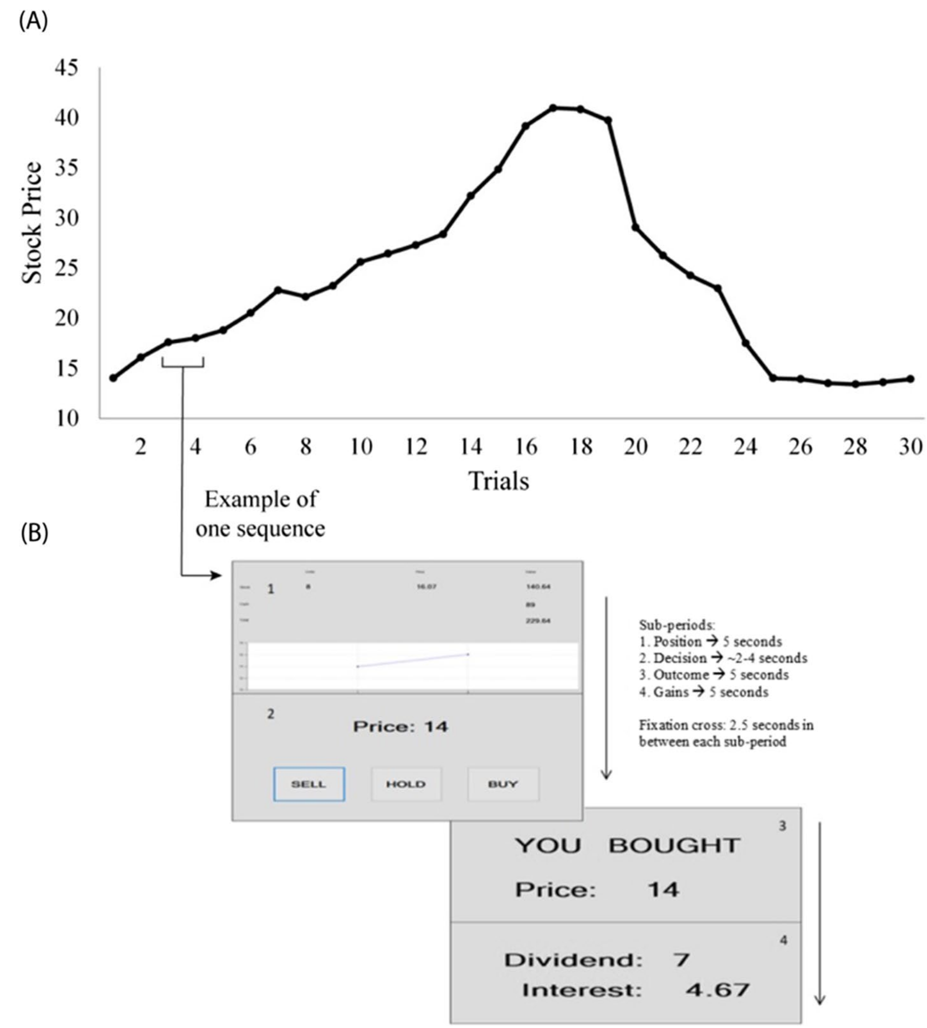

Fig. 1 Experimental software sequential images shown to subjects (from top to bottom): holdings (displaying no. of stocks held and cash), the decision-making period (where subjects decide to buy, sell or hold the stock), the outcome (re-iterating the trading decision and at what price) and the gains (stock dividend and interest from cash). Adapted from (Smith et al. 2014)

last market price. As such, buying the stock at t and selling it one period later led to the expected win of $E[P_{t+1}] - P_t + E[D]$. The same investment worth P_t in cash results in a gain in rP_t. Hence, in equilibrium, $rP_t = [P_{t+1}] - P_t + E[D]$ and therefore, $P_t = \frac{E[D]}{r} = \frac{0.7}{0.05} = 14$ is an unambiguous fundamental stock value. Thus, at any price above 14, the market is deemed an asset bubble.

The subjects signed a consent form to participate in accordance with the Declaration of Helsinki. The subjects were given experimental instructions in written form before participating in the experiment. The experimenter also reiterated all the information and presented it to the subjects before running the experiment. The participants also took a four-question test to verify their understanding of the experimental instructions. Almost all participants obtained the maximum scores.

Experimental procedure

Each participant was seated in front of a laptop approximately 50 cm from the screen. Eye movements were recorded using an eye-trip device at a sampling rate of 60 Hz. All the subjects underwent a nine-point calibration procedure with an accuracy of 0.5° before each trading round. All subjects had normal or corrected-to-normal vision.

The experimental market software was developed by the first author—Mihai Toma with the help of two developers. The task is an adaptation of the one performed by (Smith et al. 2014), with some changes: subjects traded in a simulated market where prices were generated exogenously and where subjects' trading decisions did not impact the price of the stock, and the experiment was run twice on the same set of subjects to observe learning effects between the two rounds. Eye movements were collected individually for each subject while they also had an EEG helmet positioned on their heads (Toma 2023; Toma and Miyakoshi 2021). Using the generated prices provided the advantage of simulating a realistic market in which individual investors would not impact market prices.

The experiment was run twice, with each round lasting for a maximum of 15 min. A short break of 5–10 min was taken between the experimental trials. Before running the second trial of the experiment, recalibration was performed for each subject identically as in the first session. Recalibration, short breaks, and keeping the experiment shorter than 30 min are reasonable measures for reducing measurement errors (Lahey and Oxley 2016). Moreover, (Kee et al. 2020) show that usage of eye-tracking technology does not impact the outcome of economic experiments.

Defining attention, disengagement, and arousal in the eye-tracker data

Based on the data, we calculated three variables that acted as proxies for the following:

(a) Attention, using the average distance of fixations from the center of the screen.
(b) Disengagement, using the average distance between consecutive gaze fixations.
(c) Arousal, using average pupil dilation.

We interpret the changes in eye movements as follows: the more dilated the pupil, the higher the arousal; the higher the distance of fixations from the center of the screen or among themselves, the lower the attention, and the higher the disengagement. More information on the motivation and literature behind these choices can be found in "Limitations" section.

Econometric approach

The baseline specification has the following linear panel structure:

$$Payoff_{it} = \mu_i + Arousal_{it} + Attention_{it} + Disengagement_{it} + \varepsilon_{it} \tag{1}$$

In Eq. (1), $t = 1, \ldots, T$ (time) denotes the 30 periods during the experiment (we specifically look at the Holdings and Decision-making sub-periods, more details in "Results" section), while $i = 1, \ldots, N$ (cross-sections) denote the subjects. The dependent variable represents the payoff for each subject at different timeframes, and ε_{it} is the error term.

Payoffs are measured in the experimental currency and represent the account value of each subject during each of the 30 trading periods of the experiment. For the cross-section regression, the payoff is given by the average cross-section log return of investors for each of the 30 trading periods during the holding or decision-making sub-periods. In the case of panel regression, payoffs are given by log returns for each of the 30 trading periods for each subject i.

Unlike cross-sectional analysis, the panel data approach encompasses the temporal structure of the data, which translates into more observations, variability, and efficiency. Additionally, the panel data specification can capture both common and individual behaviors.

However, shifting from a period of negative returns to a period with high returns may be slow, requiring a transition time (Hüsser and Wirth 2016). For this reason, classical estimation methods for panel data, such as fixed effects or the Generalized Method of Moments (GMM), might not capture the entire structure describing the dynamics of the payoffs. To overcome this potential issue, we test if "Attention" can act as a threshold variable in a smooth transition framework.

Thus, we use the Panel Smooth Transition Regression (PSTR) approach to study the existence of a threshold effect across pooled payoffs. It relies on the Panel Transition Regression (PTR) developed by Hansen (1999), which has the following structure:

$$Y_{it} = \begin{cases} \mu_i + \alpha_1^{'} X_{it} + \varepsilon_{it}, S_{it} \leq \tau \\ \mu_i + \alpha_2^{'} X_{it} + \varepsilon_{it}, S_{it} > \tau \end{cases} \tag{2}$$

In Eq. (2) $i = 1, \ldots, N$ and $t = 1, \ldots, T$, where N and T denote periods and individuals, respectively; the dependent variable Y_{it} is the payoff of each subject; S_{it} is the threshold variable, measured as the average distance from each fixation point and the center of the screen; X_{it} is a vector of explanatory variables; μ_i are individual-specific effects; and ε_{it} is the error term.

In the PTR model, the two groups of observations below and above the threshold value are distinct, with an abrupt transition from one regime to another. To account for smooth and gradual shifts via $j = \overline{1, r}$ transition functions across $r + 1$ distinct regimes (Gonzalez et al. 2005) proposed the PSTR model:

$$Y_{it} = \mu_i + \beta_0^{'} X_{it} + \sum_{j=1}^{r} \beta_j^{'} X_{it} F\left(S_{it}^{(j)}; \gamma_j, \tau_j\right) + \varepsilon_{i,t} \tag{3}$$

In Eq. (3), We account for r transition functions $F\left(S_{it}^{(j)}; \gamma_j, \tau_j\right)$. which are normalized to the range between 0 and 1, with three key characteristics: the threshold variable S_{it}, the location parameters τ_j and the slope of each transition function γ_j,. Following Teräsvirta (1994), we define the transition function based on the following logistic representation:

$$F\left(S_{it}^{(j)};\gamma_j,c_j\right)=\left[1+exp\left(-\gamma\prod_{l=1}^{m}(S_{it}-\tau_l)\right)\right]^{-1} \tag{4}$$

with $\gamma > 0$ and $\tau_1 \leq \tau_2 \leq \ldots \leq \tau_m$.s (Omay and Öznur Kan 2010) suggested, a value of 1 or 2 for m can capture the most common types of variation. When $m = 1$, the PSTR model follows a first-order logistic transition. In this situation, if *i)* $\gamma \to 0$, we have no transitions, and we are dealing with a standard linear model with homogenous coefficients; *ii)* $\gamma \to \infty$ the model has the structure of a PTR model of (Hansen 1999), given that the transition from one regime to another is abrupt; *iii)* if $\gamma \nrightarrow 0$ and $\gamma \nrightarrow \infty$, low and high values of S_{it} correspond to the two extreme regimes, with one smooth transition function. For $m = 2$ with $\gamma \nrightarrow 0$ and $\gamma \nrightarrow \infty$, the transition function is 1 for both low and high values of S_{it}, minimizing at $(\tau_1 + \tau_2)/2$; when $\gamma \to \infty$ we handle a PSTR with three regimes and a linear model with homogenous coefficients for $\gamma \to 0$.

We argue that the PSTR methodology has several advantages warranting its use. First, it is a well-established econometric tool that can optimally use the structure of the data. Second, it can provide both (1) a threshold acting as a neurobehavioral metric for performance and, at the same time, (2) control for the effects of other variables.

Figure 2 summarizes the experimental workflow and strategy adopted in the econometric analysis.

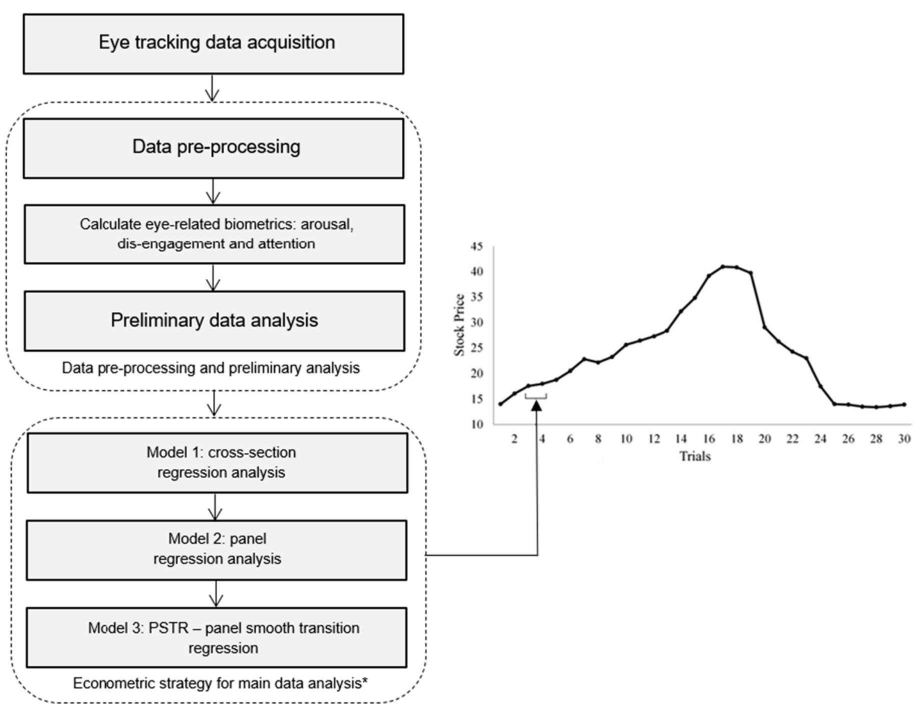

Fig. 2 Flowchart summarizing the steps of the data acquisition, preliminary analysis, and econometric strategy to model the effects of eye movements on individual returns. *Note: for all estimation procedures, we used eye-movement metrics corresponding to the Holdings and Decision-making sub-periods, as described in "Experimental design" section

Results

Summary of the physiological data and gaze behavior

We concentrate only on the Holdings and Decision-making sub-periods, which are the most relevant for trading behavior and can be closely connected to changes in eye movement variables. We calculate a 5-period moving average for each eye-tracking metric and plot the results along the stock market dynamics (Fig. 3). We calculate the moving averages to better capture highly variable eye movements and attenuate trial-to-trial volatility for better visualization alongside price dynamics. We note some interesting effects in the first trading session.

Both arousal and disengagement dynamics are consistent between the two trading sessions. In the case of the holdings sub-period, arousal shows a rapid increase in the first period, which subsided prior to the bubble peak, and a second increase synchronized with the market reaching its high and ultimately crashing again. On the other hand, we see that both disengagement and the average distance from the screen center (i.e., lack of attention) increase steadily with the market, spiking in value immediately after the bubble crash. Note, however, that (lack of) attention spiked after the bubble crash only

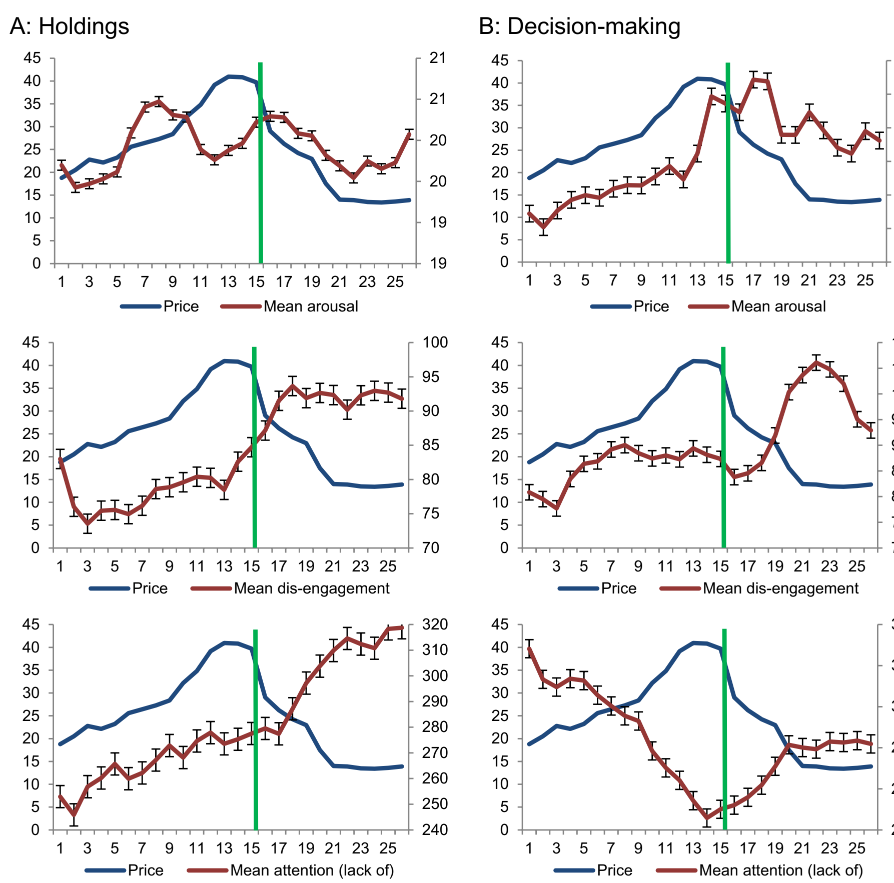

Fig. 3 Dynamics of market price and 5-period moving averages of arousal, dis-engagement and lack of attention for the holdings and decision-making sub-periods of the first trading session round. Moving averages better capture highly variable eye movements and attenuate trial-to-trial volatility to better visualize their dynamics alongside price dynamics. Bars represent standard errors. The green line marks the moment of the market crash. See the "Appendix" for dynamics of variables during the second trading session in Fig. 7

in the first trading session, and attention increased after the bubble crash when subjects knew the dynamics of the stock price in the second trading round.

For the decision-making sub-period, similar spikes were observed for arousal and disengagement. In contrast, attention increased significantly as the market price grew and the bubble increased (i.e., the average distance from the screen center decreased steadily), and subjects focused more on the center of the AOI when they had to weigh in a trading decision.

Effects of price dynamics on eye movements

Before investigating the effect of eye-tracking dynamics on individual returns (Fig. 10) in the main econometric strategy described in "Econometric approach" section, we quickly analyze whether changes influenced eye movements in and of themselves in price levels (Table 1). It could well be the case that arousal would increase at the onset of an actual bubble crash in the first run of the experiment.

We note two aspects. First, the signs between session rounds remain consistent for all variables, regardless of their magnitude. For example, price dynamics negatively influence arousal during the first trading session and have a positive influence during the second trading round. Second, statistical significance is affected from the first to the second trading round. For example, subjects did not manifest disengagement during the second round because of price dynamics. We interpret this as follows: subjects' eye movements were mainly affected by price changes during the first trading round when the information was completely new, and this effect was diminished in the second round.

Nonetheless, we treated these results and their interpretation with caution, given that (1) the experimental setup, no. of trading rounds and subjects, and (2) the fact that we used global averages in univariate regressions, which can have spurious implications. In addition, our main research question is related to the effects of eye movements on individual payoffs and how arousal and disengagement influence payoffs after a particular attention threshold point.

Therefore, we continue with the main econometric strategy using individual returns as the dependent variable and eye movements as independent variables. In the last part of the analysis, we perform a panel smooth transition regression to identify a threshold between two regimes and observe how eye-tracking data influence individual

Table 1 Elasticity coefficients of eye movements as a result of price dynamics

	First trading session round		Second trading session round	
	Holdings	**Decision-making**	**Holdings**	**Decision-making**
Arousal	− 0.0185*** (− 0.6153)	− 0.1879*** (− 4.1134)	0.0927*** (3.2708)	0.0715 (1.6575)
Attention (lack of)	− 0.3354** (− 2.4815)	0.2731* (1.9493)	− 0.2890** (− 2.1007)	0.2593** (2.6778)
Dis-engagement	− 0.5167*** (− 3.9771)	− 0.2880* (− 1.8900)	− 0.0064 (− 0.0732)	− 0.0287 (− 0.1616)

Each column provides information on the β estimate and the corresponding t-statistic of a univariate regression ran between each of the three eye-tracking metrics as dependent variables (arousal, dis-engagement, and attention) and the price returns as the independent variable. Eye-tracking variables are calculated as global averages across subjects and periods. Statistical significance at the 1%, 5% and 10% confidence levels is indicated using ***, ** and *.

performance in different regimes, thus identifying the level of attention for which arousal and disengagement could be beneficial for trading performance.

Effects of eye movements on individual returns

Effects on returns' cross-section

We run a cross-sectional regression to analyze whether and to what extent eye movements impacted average individual returns across investors. There were several interesting facts (Table 2). We also calculated the correlations among all eye-tracking variables and included them in the "Appendix" in Table 6.

First, for the holdings subperiod in both trading sessions, we observe that (lack of) attention is negatively related to individual returns. As such, individual returns are more likely to be negatively affected if participants do not pay attention. Second, for the decision-making subperiod in both trading sessions, we note that higher disengagement is correlated with lower individual returns.

Third, we find that both higher disengagement and higher arousal are positively correlated with individual returns in both trading sessions but are only statistically significant in the second trading session. As such, having already observed market dynamics, subjects were excited to anticipate the gains they would make, thus exhibiting larger pupil dilation. At the same time, given that they knew what to expect, higher disengagement is also indicative of higher returns using the same rationale. We plot the individual returns for each biometric variable in Fig. 4.

Effects on returns across subjects and time

Next, we estimate a panel regression to investigate the effects of eye movements on the conditional mean of the individual market performance. In this case, the findings are mixed (Table 3).

Table 2 Cross-section regression

Variable	First trading session		Second trading session	
	Holdings	Decision-making	Holdings	Decision-making
Intercept	0.7694 (0.4689)	0.3091 (0.1913)	− 2.3763* (− 1.8321)	− 5.9169 (− 1.2355)
Arousal	0.0210 (0.0355)	− 0.0797 (− 0.1363)	1.1139** (2.6256)	2.2115 (1.3175)
Attention (lack of)	− 0.0992* (− 1.9483)	0.0853* (1.8925)	− 0.1516** (− 2.1872)	0.2298 (1.1377)
Dis-engagement	− 0.0525 (− 0.7832)	− 0.1183*** (− 2.9154)	0.0031** (0.0532)	− 0.4544** (− 2.7179)
Adj. R-squared	21.32%	31.98%	28.86%	53.02%
Prob. F-stat	0.029	0.005	0.009	0.058
Durbin-Watson	1.35	1.35	1.80	1.41
No. obs	29	29	29	29

The table reports β estimates of exogenous variables (first column) for the log-returns as the dependent variable for both trading sessions – the holdings and decision-making sub-periods (columns 1–4). *t*-Statistics are below in parentheses. Statistical significance at the 1%, 5% and 10% confidence levels is indicated using ***, ** and *. Note: attention needs to be interpreted in reverse, as it is measured as the average distance from the center of the screen.

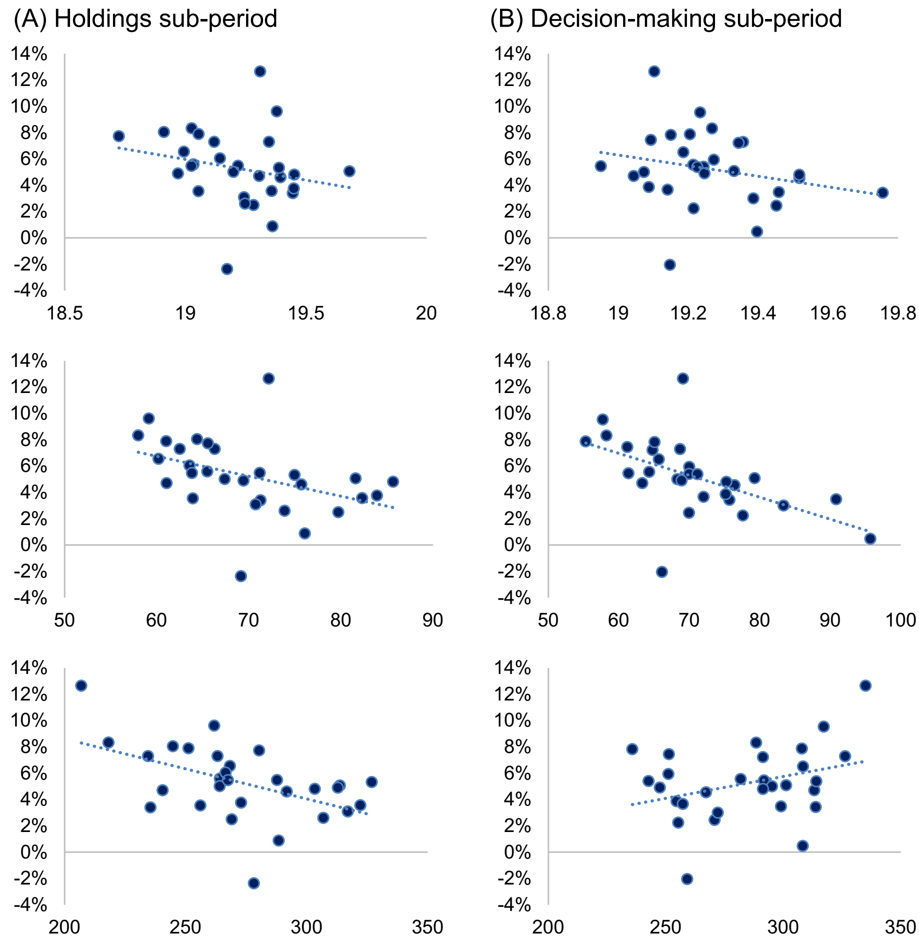

Fig. 4 From top to bottom: dynamics of arousal (pupil dilation), dis-engagement (average distance between consecutive gaze points) and lack of attention (average distance from screen center) with average cross-section individual returns for the holdings (**A**) and decision-making (**B**) sub-periods of the first trading session. See Fig. 8 from the "Appendix" for the second trading session

First, we observe that arousal negatively influences the conditional mean of the payoff in the first trading session, which is statistically significant for the holdings subperiod. This impact reversed in the second trading session. Second, disengagement negatively influenced payoffs; people with higher average gaze movements on the screen seemed to be tracked off and did not perform as well. This effect is statistically significant only in the first subperiod of the second trading session. Third, attention is a positive predictor of individual payoffs in trading sessions and sub-periods, but its effect is not statistically significant. Furthermore, we introduced the first lag of the dependent variable as exogenous in the model, as the return series are persistent in time, which is typical for financial time series (autoregressive behavior).

We also include socio-behavioral control factors in our experiment, namely, age, gender, and overconfidence, to account for potential endogeneity issues (model misspecification). As expected, overconfidence has a significant and negative effect on individual payoffs, which is in line with the findings of other studies (Barber et al. 2009). To account for potential multivariate dependencies, we estimated a centrality measure that captures

Table 3 Parameter estimates of the panel data regression model

Variable	First trading session		Second trading session	
	Holdings	**Decision-making**	**Holdings**	**Decision-making**
Intercept	0.1298 (3.3126)	0.0756*** (3.2081)	− 0.0497 (− 0.6853)	0.0512 (1.6420)
Returns(-1)	0.4818*** (46.1692)	0.4789*** (41.9444)	0.4075*** (2.9760)	0.4054*** (2.9838)
Arousal	− 0.0069* (− 1.8972)	− 0.0047 (− 1.2682)	0.0038* (1.6743)	0.0008 (0.3396)
Attention (lack of)	0.0012 (0.8246)	0.0002 (0.1371)	0.0011 (1.3885)	0.0022 (0.9264)
Dis-engagement	− 0.0010 (0.6646)	− 0.0022 (− 1.4760)	− 0.0033** (− 2.3162)	− 0.0001 (1.6035)
Age	0.0002 (0.8341)	− 0.0002 (− 0.0390)	− 0.0005 (− 0.0791)	0.0005 (0.0966)
Gender	− 0.0002 (− 0.1909)	− 0.0003 (− 0.2747)	0.0014* (1.6861)	0.0003 (0.4877)
Overconfidence	− 0.0026** (− 2.1059)	− 0.0034*** (− 2.9041)	0.0019 (− 1.6448)	− 0.0018** (− 1.9962)
Degree ranks	− 0.0136*** (2.7237)	− 0.0041 (− 1.1767)	0.0119 (1.4793)	− 0.0048 (− 1.0499)
Adj. R-squared	29.24%	28.61%	18.61%	18.38%
Prob. Wald F-stat	0.00	0.00	0.00	0.00
Durbin-Watson	2.20	2.2057	2.2481	2.2608
No. observations	729 (27 cross × 28)	756 (27 cross × 28)	728 (26 cross × 28)	728 (26 cross × 28)

The table reports β estimates of exogenous variables (first column) for the log returns (columns 1–4) as the dependent variable for both experiments—the holdings and decision-making periods. *T*-Statistics are below in parentheses. Regressions using 1st trading session data were corrected with period SUR standard errors and covariance, while 2nd experiment regressions were run using White cross-section standard errors. Statistical significance at the 1%, 5%, and 10% confidence levels is indicated using ***, **, and *. Note: attention needs to be interpreted in reverse, as it is measured as the average distance from the center of the screen

the degree of rank centrality among the biometric variables from our models, as per Giudici et al. (2020a, b). We introduce this variable into the model and observe that it is statistically significant for the first trading session's first sub-period: the higher the number of biometric indicators, the lower their influence on individual returns. In the future, we will consider alternative methods for correlation networks, such as those based on machine learning algorithms rather than regression models, as per Giudici et al. (2020a, b).

Panel smooth transition regression

Table 4 presents the results of the PSTR estimations. The impact coefficient associated with the first regime is given by the value of β_0, whereas that for the second regime is given by $\beta_0 + \beta_1$.

The nonlinear part of the PSTR model captured by β_1 indicates the extent to which the impact of arousal and disengagement on payoffs increases or diminishes when attention exceeds a certain threshold. For the first trading session, the results can be interpreted as follows: During the decision-making sub-period, arousal positively influences payoffs in the first regime (β_0) when attention is below the threshold, but in the second regime, when attention exceeds the threshold level, the impact diminishes by more than 50%

Table 4 Estimates of the PSTR model

Variable	Holdings			Decision-making		
	β_0	β_1	$\beta_0+\beta_1$	β_0	β_1	$\beta_0+\beta_1$
(A) First trading session						
Arousal variable	0.0008 (0.0374)	− 0.0114 (1.5622)	− 0.0106	0.0351* (1.7318)	− 0.021* (− 1.7835)	**0.0141**
Dis-engagement variable	− 0.0055 (− 1.5234)	0.0055 (1.0333)	0	− 0.0219*** (− 2.6387)	0.0138* (1.6780)	− **0.0081**
Wald regime test (*p* value)	0.36			0.251		
Slope (γ)	45.23			21.31		
Threshold value (c)	640.59			442.35		
(B) Second trading session						
Arousal variable	0.0522*** (4.8018)	− 0.0260*** (− 2.9818)	**0.0262**	0.0018*** (2.1099)	0.000 (0.0753)	0.0018
Dis-engagement variable	− 0.0190*** (− 4.1294)	0.0163*** (2.6717)	− **0.0027**	− 0.0003** (− 1.9762)	0.0003* (1.7209)	**0**
Wald regime test (*p* value)	0.95			0.044		
Slope (γ)	9.71			0.83		
Threshold value (c)	303.93			132.62		

The reports results of the PSTR estimation for both experiments (upper and lower sections denoted as A and B) for the first two periods: holdings and decision-making. The first two rows from both A and B report β estimates of the exogenous variables for the log returns (columns 1–4) as the dependent variable in both transition functions. Column ($\beta_0+\beta_1$) represents the effect of the corresponding variable in the second regime (i.e., when attention is above the estimated threshold) and holds only when both coefficients are statistically significant (in bold). The last three rows report information for the Wald regime test, having as a null hypothesis the existence of two threshold functions, the slope of the function (the γ variable) and the location parameter—the threshold between the two regimes. For the first trading round, attention variable is given by the average distance from the lower center of the screen and for the second trading round, attention is calculated as the average distance from the center of the screen. Statistical significance at the 1, 5 and 10 confidence levels is indicated using ***, ** and *.

(measured by $\beta_0+\beta_1$) from 0.0351 to 0.0141. At the same time, for the second trading session, during the Holdings subperiod, disengagement has a negative effect of − 0.019 on returns when attention is below the threshold, but the negative effect diminishes to − 0.0027 as attention increases.

Based on these results, several interesting effects were reported. First, we observed statistically significant and consistent effects of both arousal and disengagement during the Holdings and Decision-making sub-periods. Second, the effects are statistically significant only in the decision-making sub-period of the first trading round and the holding sub-period of the second round. Third, we find a switch in regime behavior for both arousal and disengagement in the two periods that does not affect the direction of the effects for various attention levels. Figure 5 presents the transition functions for the holdings and decision-making periods in the first trading round. Figure 6 presents a cartoon representation of the asymmetric effect of arousal and disengagement on individual returns for a given level of attention.

Results Summary

Considering the large number of estimations we performed and the various effects we identified, we summarize the results in Table 5 for an overall view. We estimate transition

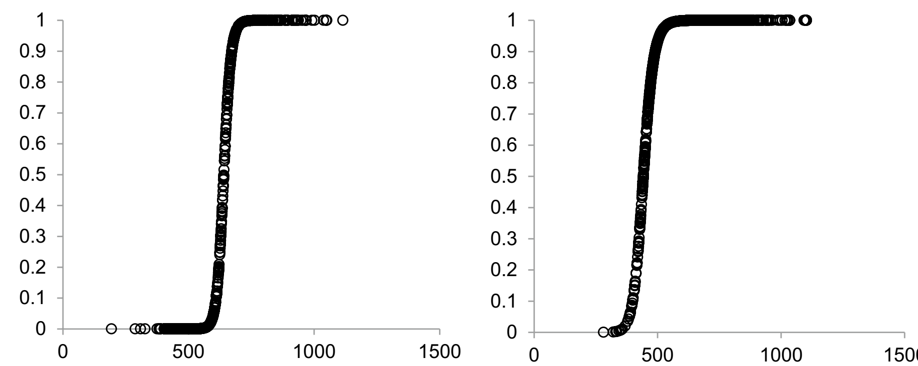

Fig. 5 Transition functions for the holdings (left pane) and the decision-making periods (right pane) when considering distance from each fixation point and the center of the screen as threshold (see Fig. 9 in the "Appendix" for the second trading session)

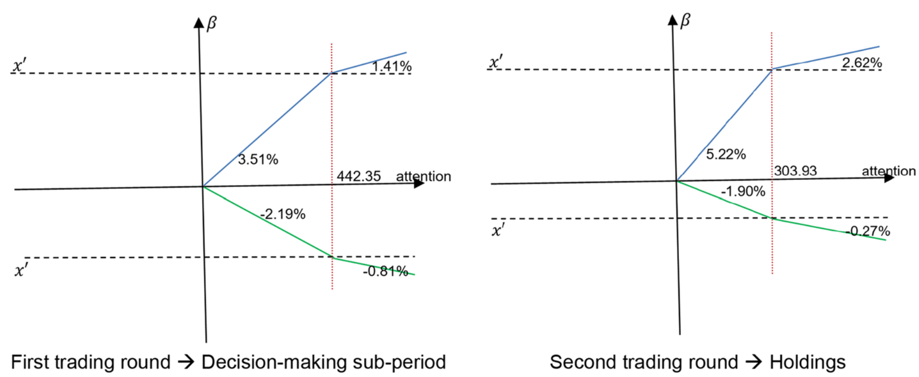

Fig. 6 PSTR results—cartoon graph of asymmetric effect of arousal (blue line) and dis-engagement (green line) on individual returns for various levels of attention (red dotted line) for the a. Decision-making sub-period during the first trading round and b. Holdings sub-period during the second trading round. The x-axis plots the attention level and the y-axis plots the β effect of arousal (positive domain) and dis-engagement (negative domain). Axes are not to scale and drawn for a better visual representation of the PSTR results

Table 5 Effects of variables summary

	Arousal		Attention (lack of)		Dis-engagement	
	Holdings	**Decision**	**Holdings**	**Decision**	**Holdings**	**Decision**
(A) First trading round						
Cross-section regression	+	−	−	+	−	−
Panel regression	−	−	−	−	−	−
PSTR	β_0	+	+	Threshold variable	−	−
	$\beta_0 + \beta_1$	−	+		0	−
(B) Second trading round						
Cross-section regression	+	+	−	+	+	−
Panel regression	+	+	+	+	+	+
PSTR	β_0	+	+	Threshold variable	−	−
	$\beta_0 + \beta_1$	+	+		−	0

Here, the signs for attention (calculated as average distance from screen center) are written opposite to β estimates to be interpreted on how attention influences returns. Please see Tables 2, 3 and 4 for coefficients and statistical significance.

functions and identify the threshold levels of attention at which arousal and disengagement have different effects on payoffs. We find various effects for all variables depending on the experimental run and the investigated market sub-period. Arousal has a higher positive impact in the first regime, with diminishing effects in the second regime, whereas disengagement negatively influences returns in the first regime, which diminishes as attention increases. These dynamics are consistent for both trading rounds.

Discussion

The literature investigating the relationship between eye movements and trading performance is scarce. We investigated how arousal, attention, and disengagement, as measured by eye movements, influence individual returns in an experimental bubble market. In this section, we discuss the obtained results and place them in the context of other studies. Below, we discuss the impact of eye movements on individual experimental returns (1) across individuals (cross-sectional analysis), (2) across individuals and time (panel analysis), and (3) in a nonlinear setting considering a specific attention threshold.

Arousal influence on individual returns

Pupil dilation has been shown to have various effects in different contexts and is an indicator of arousal, memory load, or even pain (Beatty 1982; Bradley et al. 2008). Other studies have linked pupil dilation to cognitive effort (Granholm and Steinhauer 2004; Kahneman and Beatty 1966). In this study, we define pupil dilation as a biometric of arousal, considering the nature of the boom-and-bust trading framework. Pupil dilation has long been established as a physiological marker of noradrenaline processes in the brain and body as an activation of the locus coeruleus (LC) (Joshi et al. 2016) representing a cluster of neurons in the brainstem that releases noradrenaline, which is known to increase arousal and alertness (Bossaerts 2021). Furthermore, while dopamine reward prediction errors have been linked with tasks examining how people respond to changes in expected rewards, the noradrenaline reward prediction error hypothesis can be interpreted as a parallel that can provide more insight into how risk is encoded from a neurophysiological perspective using pupil dilation (Preuschoff et al. 2011). Thus, the authors reported a correlation between risk prediction errors and pupil dilation. In the current study, the results from the cross-sectional regression suggest that arousal positively correlated with payoffs for both the holdings and decision-making sub-periods but was statistically significant only in the second trading round. However, the panel analysis indicates that arousal is only significant in the holdings subperiod in the first trading round and has a slight negative effect. For the PSTR framework, we observe that arousal is statistically significant only for the decision-making subperiod in the first trading round and the holding subperiod in the second trading round, but its effects diminish in both cases after a certain attention point.

Our results align with other studies that report a positive relationship between arousal and the expected value of gambles. For example, Glöckner et al. (2012) determined that arousal, as measured by pupil dilation and SCR, increased with the average expected value of the gambles in a condition where risky decisions are formed from the description, that is, the decision between gambles with stated probabilities and outcomes. Similarly, Fiedler and Glöckner (2012) reported that gambles with a mean expected value resulted in longer decision times and greater arousal (i.e., pupil dilation). A higher propensity to invest in higher expected value gambles is similar to taking on more risk, especially in a bubble market.

Arousal has also been used as a marker for affective information in a financial investment experiment by Rubaltelli et al. (2016), who showed that larger pupil dilation was correlated to a higher willingness to invest in funds regardless of past performance.

In the PSTR framework, when considering attention as a threshold variable, we find that arousal positively influences payoffs for both the holdings and decision-making subperiods in both trading sessions. For the first trading round, the effect of increased arousal is statistically significant only during the decision-making subperiod. When attention is lower, arousal positively influences returns that decrease but remains positive when attention increases and surpasses the estimated threshold. For the second trading round, we observe the same effects, namely that arousal positively predicts the individual returns of participants with a lower attention level; this effect diminishes as attention increases above the threshold but remains positive. Given that subjects had already observed price dynamics, this might be interpreted as anticipatory excitement towards making more gains, regardless of attention level. Even though the bubble was exogenously generated in this experiment, such anticipatory excitement can be interpreted as a self-reinforcing mechanism for overconfident behavior leading to a potential bubble build-up (Haracz and Acland 2015). At the same time, positive effects of arousal throughout different levels of attention could also indirectly be related to gut-feeling decision-making, being interpreted as such: the more attention participants pay and the more they are excited by gain perspectives, subjects experience a positive internal gut feeling of making more money in the market (Bossaerts 2021), associated with having learned market dynamics. However, in the case of increased arousal during decision-making while first experiencing the bubble, it can be interpreted as decision uncertainty driving rapid changes in pupil-linked arousal, thereby shaping ongoing stock trading behavior (Urai et al. 2017). Overall, our findings indicate that arousal has a higher positive effect on payoffs when attention is below the estimated threshold and a lower yet still positive effect when attention levels are above the threshold across participants for the 30 trading rounds.

Gaze distance for attention and dis-engagement

Our results show that subjects pay attention to the stock price, the amount of which positively correlates with individual returns when subjects look at the stock price graph but not when looking at the actual buttons warranting the trading decision. Across individuals, (lack of) attention (proxied by average distance from screen center) is negatively correlated with returns during the Holdings sub-period in both trading sessions and positively correlated with stock returns during the decision-making sub-period in both trading sessions. As expected, the more attention participants paid while seeing stock price dynamics, the higher their returns. However, in the panel framework, aggregating across subjects and time is always a positive predictor of returns but is not statistically significant.

However, in the PSTR framework, after certain threshold levels of attention are reached, we observe statistically significant effects of both arousal (positive) and disengagement (negative) on individual returns. If arousal and disengagement are only statistically significant for the decision-making subperiod in the first round, they are only significant for the holding subperiod in the second round (see Table 4 for more details). Hence, after having learned market dynamics, anticipating the button press weighed more than the actual decision.

In the PSTR framework, disengagement negatively affects payoffs that vary with attention levels; the more attention participants paid, the less disengagement detrimental to them, making gains. Disengagement has a negative impact that decreases but remains negative as attention increases above the threshold. This effect is higher for the Holdings subperiod of the second trading round and diminishes in the decision-making subperiod of the second trading period, where it becomes no longer significant.

It is undeniable that attention plays an essential role in trading, most notably because individuals have limited cognitive capacities in processing high volumes of information (Li and Camerer 2019; Khaw et al. 2021; Frydman and Jin 2021). Our results align with those of other studies that have investigated attention with eye tracking. For example, using eye-tracking, it has been shown that traders spend more time looking at particular sections of a stock's graph, such as the top of the stock graph (George and Hwang 2004), the bottom (Huddart et al. 2009) or the last trading day(s) of the stock (Duclos 2015), thus attributing more attention to it (Li and Yu 2012). However, while the above studies focused on measuring attention using the time spent in particular areas of interest, we took a different approach. We used the average gaze distances from the main focal point of the task (i.e., the stock graph and decision-making buttons for trading). We motivated our choice based on the following:

(a) For the holding sub-period, subjects only saw numbers depicting their account value and did not receive any visual stimuli for which the time spent looking at might have influenced their subsequent decisions, as is the case in consumer behavior (Gidlöf et al. 2017). In addition, the subjects were instructed to fixate on the screen (and hence look at the graph) for only 5 s for the EEG experiment. The duration of the fixation period is insufficient to provide adequate measurements from the perspective of time spent on a specific area of attention but rather from the perspective of rapidly moving their eyes on the screen to check the stock price, no stocks owned, or account value.

(b) For the decision-making period, there are significant discrepancies between subjects in terms of reaction time to trade the stock, which might deem the time spent on AOI to not be relevant or statistically significant, as opposed to the average distances from the center. Indeed, after reviewing the data on time spent on AOI, we observed very large differences between subjects and could not validate the data statistically.

(c) Findings from the literature: Orquin and Mueller Loose (2013) underlined that fixation time on a specific stimulus could be independent of decision-making outcomes. Also, Russo and Rosen (1975) showed that participants usually compare spatially proximate alternatives to minimize attention costs, while Ballard et al. (1995) explained that the number of transitions between stimuli is reduced when spatial distance is increased. Thus, in a risk-taking task such as ours, where some level of anxiety may be induced, the distance between fixations can be considered an adequate alternative.

Limitations

The relatively low number of participants was the main limitation of the current study. Nonetheless, a posterior power analysis (Faul et al. 2007, 2009) with an $\alpha = 5\%$, and $\beta = 20\%$ for a sample size of 27 subjects revealed a power of 82% for statistical inference. In addition, Friston (2012) also stipulated that 16–32 subjects represent an optimal sample size for neuroimaging and psychology studies. The other limitation comes from the hardware solution used, such as restriction of head mobility for the sake of ecological validity and lack of autonomic nervous system measurements, such as skin conductance response for evaluating arousal levels. Nonetheless, we believe our finding has unique value as one of the first of its kind.

Future directions

Could eye tracking be used in the future as a tool to improve financial trading skills? Can it be used to enhance decision-making? Answers to these questions have already been provided and seem positive. For example, neuroexperimental training using eye-tracking and machine learning as augmentation platforms for individuals in their decision-making processes has been developed (Cinel et al. 2019).

Recently, Bossaerts et al. (2020) replicated the original study of Smith et al. (2014), on which this study is based, and determined that heart rate changes of subjects anticipating trading at higher prices (in the bubble) lead to higher earnings and that trades precede heart rate changes and earnings decrease. They also found that subjects with higher skin conductance responses to stock market holdings have higher earnings. These findings encourage future studies to evaluate autonomic nervous system functions during trading tasks to obtain physiological evidence of arousal that can be used to interpret behavioral data from the viewpoint of internal decision-making processes.

Additionally, technology and simplified market interfaces can lead to performance increases, as Teschner et al. (2015) suggested. The advantages of neurophysiological biometric data such as electrocardiogram, eye-tracking, and EEG systems have the potential to take individual-level training in cognitive reasoning and decision-making to the next level. Such training could focus on improving attention, calibrating risk-taking behavior, and improving mental workload, memory, reflexes, and even learning tasks (Rosch and Vogel-Walcutt 2013). The econometric methodology offers a clear advantage: we can state whether and to what extent changes in eye movements positively or negatively impact individual gains. Moreover, after what level of attention do these effects increase or decrease?

We speculate that the attention threshold can be leveraged as a neurobehavioral metric to predict successful trading outcomes. Although our estimates are provided ex-post, the results in this study can lead to the design of other platforms in which real-time eye-tracking and neural measurements can provide triggers to users, alerting them with regard to their attention level while also controlling for specific individual socio-behavioral traits. This would act as a platform for real-time monitoring of similar performance-dependent tasks (Friedrich et al. 2017). In the future, we aim to develop experiments in which subjects can calibrate and improve their decisions by monitoring the previous eye movements of experts in such tasks by also using machine-learning algorithms, a methodology also explored by Król and Król (2019b).

Furthermore, considering the rich datasets provided by such methods, machine-learning algorithms that warrant the use of big data are a natural complementary method for analyzing behavior. Based on preliminary work by Król and Król (2019b), we aim to further enhance the paradigm of financial risk-taking in order to better calibrate risk-taking behavior using a mix of neural and eye-tracking data coupled with AI and ML algorithm development for real-time learning. Considering recent increases in black-box approaches in developing ML models, we will also consider the issue of explainability in machine learning (Giudici and Raffinetti 2021), thereby ensuring that, when developed, these platforms are well understood by practitioners and stakeholders. A multidisciplinary platform of this type could serve individuals to calibrate their risk-taking behavior better. Such platforms leveraging human data can not only be beneficial for consumers to understand their behavior better and ultimately provide complementary ways for companies to optimize their processes and even predict bankruptcies (Kou et al. 2021a, b). In the future, we want to leverage biometric information such as neural data or eye tracking to understand better how individuals allocate risks in portfolio formation. This aspect is becoming more important, especially in the recent MiFID II developments on real-time monitoring of risk-taking positions. Moreover, considering the recent development of the fintech sector, hybrid human–computer approaches to financial innovations could be warranted for enhanced decision support systems alongside statistical and ML approaches (Kou et al. 2021a, b).

The current study serves as a proof of concept for future studies that can utilize both neural and eye-tracking data, measured simultaneously, to provide more in-depth information on faulty decision-making and how it can be improved. Decision-making optimization is mostly required in highly cognitively demanding professions such as C-level executives, managers, surgeons, or pilots. An immediate and natural application of such a platform for improving decision-making processes is in organizations for managers, as shown by Chen et al. (2015) and Kramer and Maas (2020).

Conclusions

This study reports the results of an experiment in which subjects maximize payoffs by trading a risky asset in a simulated experimental asset bubble market. Using eye tracking, we compute three proxy variables to measure arousal, attention, and disengagement and subsequently estimate how these inferred cognitive states influence individual trading returns. Attention is positively correlated with individual returns when subjects look at a stock price graph. Arousal positively impacts returns, which decreases as attention increases above the threshold but remains positive overall. Disengagement negatively impacts returns when attention is below the threshold, and its effect diminishes as attention increases above the estimated threshold. These tendencies are consistent in both trading rounds and for both subperiods (Holdings and Decision-making), suggesting that arousal, disengagement, and attention play crucial roles in predicting successful trading.

We conclude that eye tracking is a versatile tool that can facilitate the inference of cognitive states to better understand financial decision-making with the potential to improve trading performance if leveraged in appropriate experimental frameworks. Further experimentation is required in this field to bridge human–computer interactions.

Appendix

See Figs. 7, 8, 9, 10 and Table 6.

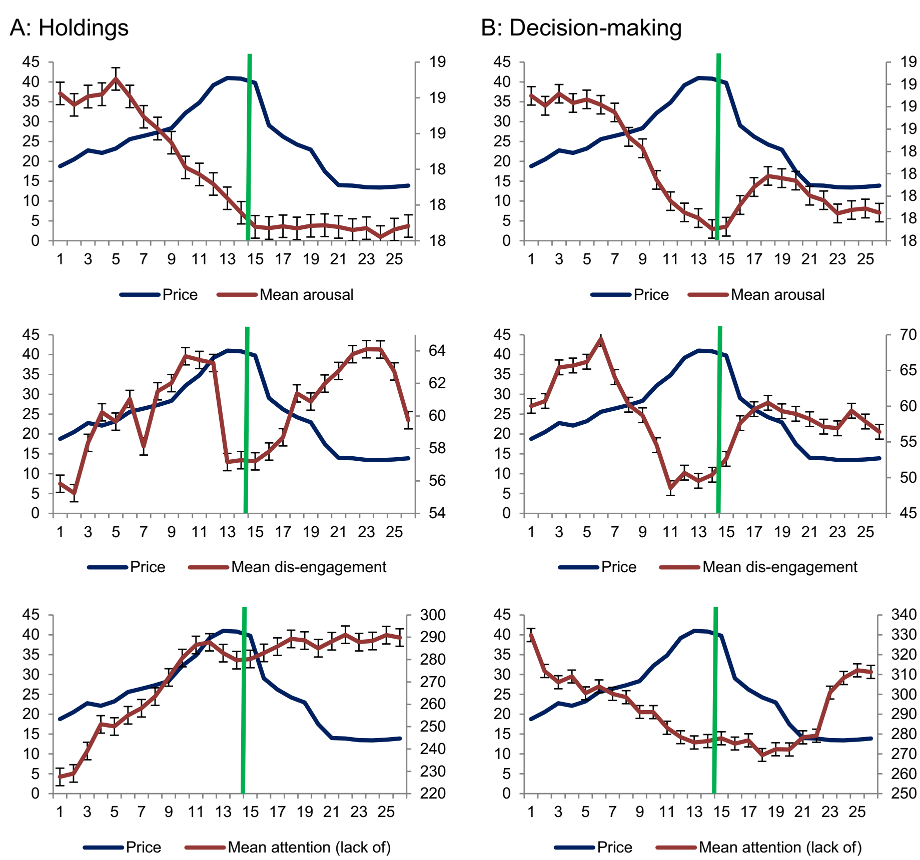

Fig. 7 Dynamics of market price and 5-period moving averages of arousal, dis-engagement and lack of attention for the holdings and decision-making periods of the second trading session round. Bars represent standard errors. The green line marks the moment of the market crash

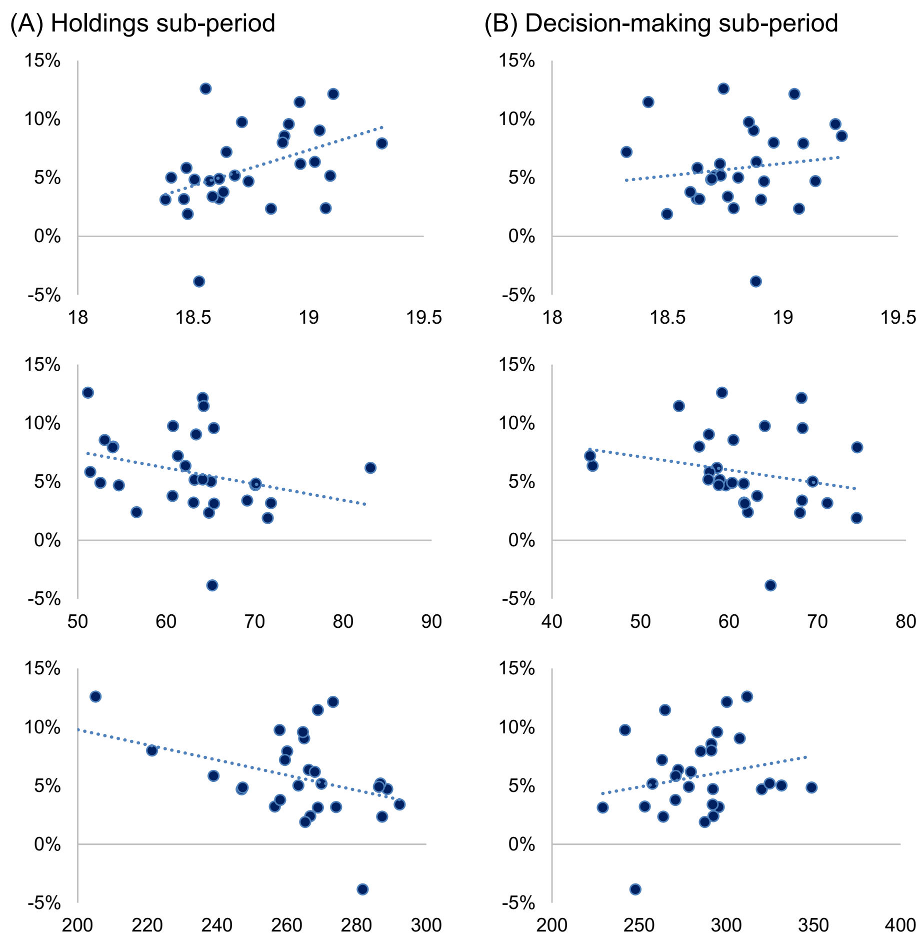

Fig. 8 From top to bottom: dynamics of pupil dilation, dis-engagement and lack of attention with average cross-section individual returns for the holdings (**A**) and decision-making (**B**) sub-periods of the second trading session

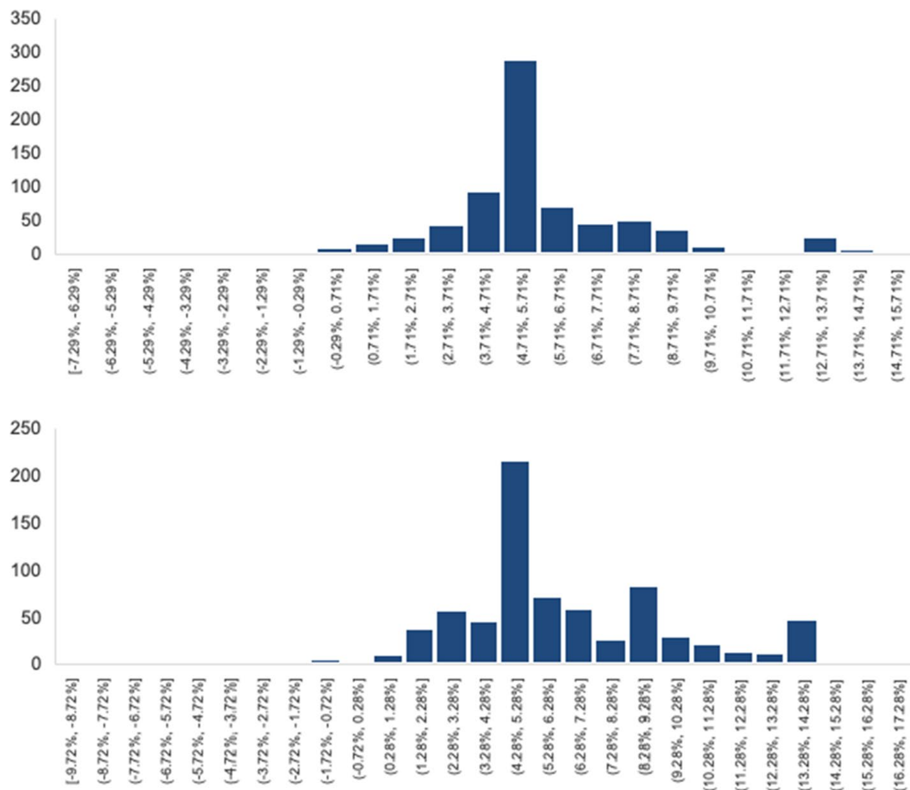

Fig. 9 Distribution of returns for the first trading session (upper pane) and second trading session (lower pane)

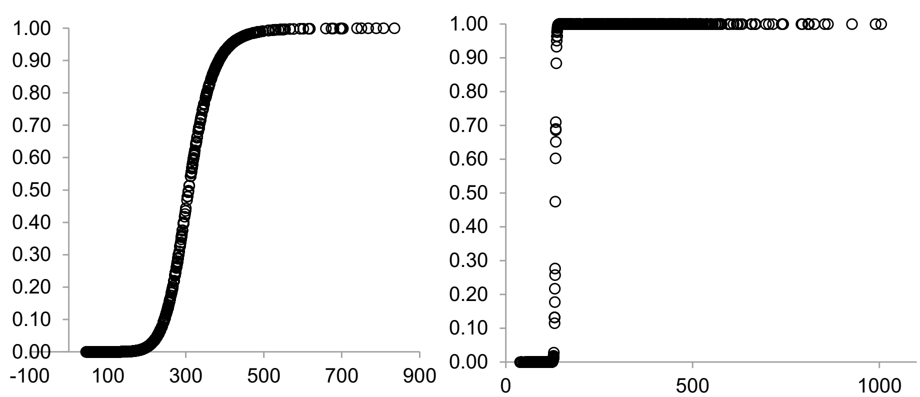

Fig. 10 Transition functions for the holdings (left-pane) and the decision-making periods (right pane)

Table 6 Correlation matrix of eye-tracking variables for:

	Arousal (%)	Dis-engagement (%)	Attention (lack of) (%)
(A) Holdings sub-period in the first trading session			
Arousal	100	− 9	5
Dis-engagement	− 9	100	22
Attention (lack of)	5	22	100
(B) Decision-making sub-period in the first trading session			
Arousal	100	− 9	16
Dis-engagement	− 9	100	22
Attention (lack of)	16	22	100
(C) Holdings sub-period in the second trading session			
Arousal	100	− 28	− 16
Dis-engagement	− 28	100	30
Attention (lack of)	− 16	30	100
(D) Decision-making sub-period in the second trading session			
Arousal	100	− 15	− 6
Dis-engagement	− 15	100	16
Attention (lack of)	− 6	16	100

Abbreviations

AOI	Area of interest
EEG	Electroencephalography
PTR	Panel Transition Regression
PSTR	Panel Smooth Transition Regression

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Author contributions
Conceptualization: F-MT; Data curation: F-MT; Formal analysis: F-MT, C-OC, MK and MM; Investigation: F-MT, C-OC, MK and MM; Project administration: F-MT; Supervision: F-MT; Methodology, F-MT; Software, F-MT; Validation, F-MT, C-OC, MK and MM; Writing—original draft preparation: F-MT; review and editing, F-MT, C-OC, MK and MM All authors read and approved the final manuscript.

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Availability of data and materials
The datasets generated and/or analysed during the current study are not publicly available due to privacy constraints, but are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
We confirm that the manuscript has been submitted solely to the Financial Innovation and that it is not published, in press, or submitted elsewhere. We also confirm that all research meets the ethical guidelines, including adherence to the legal requirements of the studied countries. We confirm that we have seen, read, and understood the guidelines on copyright. Informed consent was obtained from all subjects involved in the study.

Competing interests
The authors declare that they have no competing interests.

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