OUKA
The University of Osaka
Institutional Knowledge Archive

Title	Trading institutions, emotional arousal, and overbidding
Author(s)	Corgnet, Brice; Cornand, Camille; Hanaki, Nobuyuki
Citation	Journal of Economic Dynamics and Control. 2026, 190, p. 105382
Version Type	VoR
URL	https://hdl.handle.net/11094/106294
rights	This article is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.
Note	

The University of Osaka Institutional Knowledge Archive : OUKA

https://ir.library.osaka-u.ac.jp/

The University of Osaka

Journal of Economic Dynamics & Control 190 (2026) 105382

Contents lists available at ScienceDirect

Journal of Economic Dynamics and Control

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

Trading institutions, emotional arousal, and overbidding☆

Brice Corgnet [a], Camille Cornand [b], Nobuyuki Hanaki [b,c,*]

[a] Emlyon Business School Université Lumière Lyon 2 Université Jean Monnet Saint-Étienne GATE, CNRS, Lyon, France
[b] GATE, CNRS Université Lumière Lyon 2 Université Jean-Monnet Saint-Étienne Emlyon Business School, Lyon, France
[c] Institute of Social and Economic Research, The University of Osaka, Ibaraki, Osaka, Japan and University of Limassol, Limassol, Cyprus

ARTICLE INFO

JEL codes:
C91
C92
G41
D91

Keywords:
Competitive arousal
Trading institutions
Feedback
Emotions and risk

ABSTRACT

We investigate the influence of trading institutions on emotional arousal and bidding behavior through a series of behavioral and physiological experiments involving an investment task. In line with the competitive arousal hypothesis, we show that market institutions exacerbate the emotional arousal associated with winning bids, especially when buying an asset leads to substantial earnings. The market treatment exhibits stronger overbidding and bubble dynamics than baselines that use a Becker-DeGroot-Marschak mechanism. Treatment differences disappear for investors who exhibit no base rate emotional arousal. Our study shows that emotions are an important mechanism for understanding market outcomes and suggests designing new trading institutions to mitigate competitive arousal and subsequent overbidding in markets.

1. Introduction

1.1. Emotions in markets

As an essential tool for the allocation of resources, markets are the cornerstone of modern economies. Yet, they are complex systems whose behavior has been difficult to decipher. Markets are unexpectedly volatile (Shiller, 1981a, 1981b, 1992), and tend to repeatedly produce mispricing patterns in the form of bubbles and crashes (Smith et al., 1988; Sornette, 2009; Aliber et al., 2023; Greenwood et al., 2019). Although economists and finance scholars continue to debate the extent of these anomalies (Fama, 2014), few would dispute that market prices can at times fail to reflect all available information. However, if market prices do not perfectly reflect fundamental information, to what factors are they responding?

To answer this question, numerous works have emphasized investors' biases in assimilating new information. These biases have been modeled as failures to apply Bayesian updating, relying instead on heuristics that give excessive weight to small samples (Rabin, 2002) and to any information confirming one's prior beliefs (Daniel et al., 1998). Other papers have emphasized people's inability to extract information from market signals (Hong and Stein, 1999; Corgnet et al., 2018; Eyster et al., 2019).

Although previous research has emphasized cognitive limitations as the main driver of mispricing (Akiyama et al., 2017; Bosch-Rosa et al., 2018), a few exceptions in the literature have considered the role of emotions. For example, Andrade et al. (2015) have shown that inducing certain emotions, like excitement, can increase mispricing in experimental markets. Using a similar setup, Breaban and Noussair (2017) have assessed traders' emotional state using face-reading software and found that price levels were lower

☆ The baseline design of the experiment reported in this paper has been approved by the IRB of INSERM (#18–493).

* Corresponding author at: Institute of Social and Economic Research, The University of Osaka, Ibaraki, Osaka, Japan.
E-mail addresses: corgnet@em-lyon.com (B. Corgnet), cornand@gate.cnrs.fr (C. Cornand), nobuyuki.hanaki@iser.osaka-u.ac.jp (N. Hanaki).

https://doi.org/10.1016/j.jedc.2026.105382
Received 30 October 2025; Received in revised form 18 June 2026; Accepted 25 June 2026
Available online 27 June 2026
0165-1889/© 2026 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC license (http://creativecommons.org/licenses/by-nc/4.0/).

(higher) when people entered the market in a more fearful (happier) emotional state. The literature on emotions in markets remains scant because of the technical challenges associated with measuring emotions. Yet, a recent study by Bossaerts et al. (2023) uses physiological recordings to assess traders' arousal over the course of a market experiment. They show that anticipatory reactions measured using heart rate recordings can predict traders' earnings. These findings extend prior empirical research using non-experimental methods (see, e.g., Lo and Repin, 2002; Shefrin, 2007; Lo et al., 2005).

The dearth of research on the impact of emotions in financial markets contrasts with historical accounts of market booms and busts, which emphasize the key role of animal spirits (Keynes, 1936), exuberance (Shiller, 2015), and manias (Aliber et al., 2023). This emotion-focused rhetoric is also found in behavioral finance writings that refer to emotions such as greed and fear (Shefrin, 2007; Lo, 2013) and market sentiment as critical predictors of financial outcomes (Baker and Wurgler, 2007). However, emotions are very rarely measured, and even less often manipulated, in a market context. Since the finance literature on emotions remains in its infancy, we ask a foundational question: are emotions relevant to financial markets? In doing so, we also ask whether markets produce specific emotional reactions that are not observed in related institutions and that impact trading outcomes.

One distinct feature of the market institution is its social dimension, which has long been recognized by anthropologists, who view markets as one of the four basic social relationships (Polanyi, 1944; Fiske, 1991; Sahlins, 2013). The recognition of the social dimension of markets has led to the emergence of the field of social finance (Shiller et al., 1984; Hirshleifer, 2020; Kuchler and Stroebel, 2021). Along with their social dimension, markets are characterized by their competitive nature. To study market-specific emotions, we thus causally manipulated both the social and competitive dimensions of the trading institution. Our approach differs sharply from Andrade et al. (2015), which is the only study we are aware of that causally manipulates emotions in markets. Because these authors induce moods with video clips, as is often done in psychology (Rottenberg et al., 2007), their focus was on generic emotions such as excitement, sadness, and fear. By contrast, we manipulate key institutional features of markets – their social and competitive dimensions – and assess how those dimensions impact emotional arousal and market outcomes.

Beyond answering our foundational question, our approach can offer practical insights because trading institutions, unlike emotions that are deeply rooted in our evolutionary past (Damasio and Carvalho, 2013; Plutchik, 2001), can be reshaped more easily. It follows that if certain emotions induce excessive mispricing, it would be most effective to design a new trading institution that tames those emotions rather than attempting to control the emotional response of individual investors.

1.2. *Our physiological study*

Our aim is to compare trading institutions and assess whether markets hinder or exacerbate traders' emotional reactions and subsequent bidding behavior. To compare trading institutions, we employ a between-subjects experimental design with three treatments: baseline, baseline-feedback, and market. Inspired by Corgnet et al. (CCH 2024a), the baseline features an individual investment task, in which investors bid, through a standard incentive-compatible Becker-DeGroot-Marschak (BDM 1964) mechanism, over 300 periods for a financial asset that delivers a small positive reward (either 10¢, 20¢, 30¢, 40¢ or 50¢) in more than 99% of the cases and a large loss (1000¢) otherwise. Emotional reaction is physiologically measured during the experimental task for more than half of our subjects using electrodermal conductance. The baseline-feedback treatment is the same as the baseline except that investors can observe others' bids in the previous period. The baseline-feedback treatment is used as a control that can be directly compared to the market treatment because both give investors the same information about others' bids. The market treatment thus differs from baseline-feedback only in the institution used to purchase the asset. In the market treatment, we replace the uniform draw over the prices of the BDM mechanism by a uniform draw over the bids of the participants as in a random n^{th}-price auction to determine the price of the asset (see Shogren et al., 2001). According to standard expected utility predictions, the baseline and market treatments should lead to the same bidding behavior. In contrast with this prediction, relying on the behavioral literature, we develop three hypotheses stating that treatment differences will emerge due to the presence of feedback and the competitive nature of markets.

In Hypothesis 1, we posit that bids in the baseline-feedback treatment will be higher than in the baseline treatment due to the peer effects associated with social feedback widely observed in the literature (Corazzini and Greiner, 2007; Kirchler et al., 2018; Lahno and Serra-Garcia, 2015; Kuziemko et al., 2014; Dijk et al., 2014; Fafchamps et al., 2015; Lindner et al., 2021; Gortner and van der Weele, 2019).

In Hypothesis 2, we predict differences between the market and two baseline treatments due to the impact of market competition on the emotional arousal of bidders. Competition, defined as the pursuit of scarce and contested assets (Deutsch, 1949; Malhotra, 2010), is a distinctive feature of markets compared to individual decision making in the baseline and baseline-feedback treatments. In line with the *competitive arousal hypothesis* (Ku et al., 2005; Malhotra, 2010; Adam et al., 2015), we posit that competition will exacerbate the emotional arousal associated with buying an asset and foster overbidding. Because competitive cues are, by design in our experiment, more pronounced in the market treatment than in the two baseline treatments, the competitive arousal hypothesis suggests that bids will be higher in the market than in the baseline and baseline-feedback treatments.

As a direct test of the competitive arousal hypothesis, we tested an additional Hypothesis 3. Hypothesis 3i states that emotional arousal will be higher in the market treatment after a winning bid than in the two baseline treatments. Furthermore, we test whether heightened emotional arousal can account for the higher levels of bids in the market treatment compared to the two baselines. Hypothesis 3ii posits that investors who exhibit a high level of base rate emotional arousal will bid higher in the market than in the baseline and baseline-feedback treatments, whereas no treatment differences will be observed for investors who exhibit a low level of base rate arousal.

In a series of experiments conducted with 560 participants, we find that feedback has only a minimal impact on bidding behavior, thus leading us to reject Hypothesis 1. We find support for Hypothesis 2 because overbidding is more pronounced in the market than in

the baseline and baseline-feedback treatments. In line with Hypothesis 3i, we find that emotional arousal, as measured using electrodermal activity (as in CCH) is substantially higher in the market than in the baseline treatments after winning bids, while no differences are observed after non-winning bids. Exploring the competitive arousal hypothesis further, we also show that the increase in arousal due to winning bids in the market treatment is more pronounced when the asset's payoff was high. This shows that trading in a market —an institution combining competition and endogenous allocation— rather than in a non-market institution can exacerbate the emotional arousal associated with material gain, which can be interpreted as a physiological manifestation of greed (Seuntjens et al., 2014, 2015). In line with Hypothesis 3ii, treatment differences in bidding behavior are only observed for investors who exhibit a high level of base rate arousal. In a final exploratory analysis, we show that investors exhibiting high base rate emotional arousal earn less and are more likely to go bankrupt.

1.3. Contributions

1.3.1. Overbidding in auctions

Our study of the causal impact of the market institution on emotional arousal contributes to several strands of the literature. In the auction literature, our approach sheds new light on the overbidding anomaly (for a review, see Cooper and Fang, 2008; Kagel and Levin, 2016). In line with previous research using first-price auctions (e.g., Cox et al., 1988; Goeree et al., 2002) and second-price auctions (Kagel et al., 1987; Cooper and Fang, 2008; Tan, 2020), we report stronger overbidding in a random n^{th}-price auction (relative to non-market allocation mechanisms). Stronger overbidding is consistently observed over 300 consecutive periods, thus downplaying explanations of the phenomenon based on participants' early lack of understanding and later learning (Kagel et al., 1987; Georganas et al., 2017). Our findings show that a strong overbidding is likely due to competitive arousal, which is inherent in auctions. If associated with higher stress levels, exacerbated emotions in auctions could also impair cognitive functions (Shields et al., 2016) and mediate the effect of inattention, which has been identified by Malmendier and Lee (2011) as a main driver of overbidding. Social feedback alone does not explain overbidding. These findings offer new insights into the results in Delgado et al. (2008), who emphasize the role of social competition. In our design, we can isolate the social impact of the trading institution from the competition dimension by comparing the baseline-feedback and market treatments. We show that in the absence of competition, bids align more closely with the risk-neutral valuation of the asset, even in the presence of social feedback. We thus highlight the role of competition over social feedback.

1.3.2. Emotions in markets

The finance literature on emotions is scant and has not addressed the impact of trading institutions on emotional reaction.[1] Our work demonstrates that trading institutions play an important role in explaining investors' emotional arousal and that emotions are an important determinant of overbidding in markets. Importantly, traders who display reduced base rate emotional arousal do not exhibit substantial overbidding in the market treatment. These findings relate to models of overbidding that rely on emotions such as regret (Engelbrecht-Wiggans and Katok, 2006, 2008), spite (Bartling and Netzer, 2016; Kirchkamp and Mill, 2021; Mill and Morgan, 2022), and loss contemplation (Delgado et al., 2008). However, the type of emotion we identify differs from those considered in previous works because it specifically relates to the "joy of winning" rather than the disappointment of losing (Delgado et al., 2008).

Furthermore, our approach posits that the arousal experienced following winning bids leads investors to increase their subsequent bids out of excitement. This mechanism differs from the previous models based on regret, spite, or loss contemplation that consider anticipated emotions as part of the utility function.

1.3.3. Financial bubbles

Our results also provide insights into another prevalent mispricing phenomenon: financial bubbles. Interestingly, we show that, even in the absence of retrading and speculative motives, bubble and crash patterns can be observed in all our trading institutions and are exacerbated in markets. Unlike the dominant speculative hypothesis, our results show that the competitive nature of the market, along with the competitive arousal exhibited by human traders, can exacerbate bubbles and crashes.[2] Our findings thus show that the increased emotional arousal inherent in market competition can generate mispricing, hence complementing the literature on financial bubbles.

1.3.4. Competitive arousal

Finally, our study provides a direct test of the competitive arousal hypothesis by exogenously manipulating competition and measuring physiological arousal. Our results demonstrate the moderating role of emotional arousal on bidding behavior and the relationship between arousal and the joy of winning (Cox et al., 1988). Furthermore, we reveal that the joy of winning may also relate to greed (Seuntjens et al., 2014, 2015) because the emotional arousal triggered by winning bids in the market treatment is more pronounced when asset payoffs are high. To our knowledge, the only other direct tests of the competitive arousal hypothesis in the

[1] One exception is Breaban et al. (2022), who compare first-price and Dutch auctions. However, they do not consider non-auction institutions and thus do not analyze the distinct effect of markets.

[2] Although dominant, the speculative hypothesis was challenged by Lei et al. (2001), who show that bubbles could be observed even in the absence of retrading of shares using an experimental setup à la Smith et al. (1988). However, the follow-up studies of Tucker and Xu (2024a, 2024b) show that carefully removing speculative motives does indeed eliminate bubbles.

literature are Adam et al. (2015) and Teubner et al. (2015), who manipulate rivalry by replacing human bidders with computerized bidders in experiments using English and first-price sealed-bid auctions, respectively. They found that prices were higher when bidders competed with other human bidders than when competing with computers, and their arousal, as measured by heart rates and electrodermal activity in both studies, was higher when competing with other human bidders. However, unlike our study, the manipulations of Adam et al. (2015) and Teubner et al. (2015) do not directly impact competition but only the social dimension of competition, as the authors duly acknowledge.

2. Design

We design an incentivized experiment that allows us to observe participants' behavioral and physiological reactions to the realization of financial gains and losses in an investment task across trading institutions. We use three treatments (baseline, baseline-feedback, and market treatments) to disentangle the effects of social information and competition on investors' bidding behavior. The experiment consisted of two parts. In Part 1, participants earned money by responding to a survey eliciting various psychological and cognitive characteristics (see Section 2.4). In Part 2, participants played a repeated investment task under the three treatments in a between-subjects design (see Sections 2.1 and 2.2). In addition, in order to capture the role of emotions across trading institutions, we recorded physiological measures while participants played the investment task for half of the sessions (called Baseline physio, Baseline-Feedback physio and Market physio treatments, see Section 2.3). The protocol is described in Section 2.5.

2.1. Investment task (baseline)

The design of the investment task of the baseline (Part 2) is taken from CCH. We elicited participants' willingness to pay for the asset using the BDM method. At the beginning of each of the 300 periods, participants had to bid on a financial asset that delivered a small positive reward (10¢, 20¢, 30¢, 40¢, or 50¢ with the same probability) in 99.33% of the cases and a very large loss (1000¢) otherwise. Participants did not know exactly the probability distribution behind rewards and thus made their bid under ambiguity. The expected price of the asset was 23.2¢ and would have been 30¢ if the probability of the large loss had been set to zero.

While rare, very large losses represent a standard feature of assets in financial markets. Primarily, we introduce this feature to maintain participant engagement throughout the 300 periods, ensuring the validity of our physiological measurements over the course of the experiment (see Section 2.3).[3] Beyond large losses, our design also implies frequent small losses, with a bidder purchasing the asset losing money in 22.4% of cases. This frequency of loss is comparable to that experienced by a stock market investor when calculating portfolio losses over a one-year period.

The bid (any integer between 0 and 50) in each period was compared to a price (also an integer) randomly drawn from a uniform distribution between 1 and 50.[4] If a participant's bid was greater than or equal to that price, the participant paid the price and purchased the asset. Otherwise, they did not purchase the asset.

At the end of each period, a feedback screen informed participants about the reward of the financial asset, their earnings for the current period and accumulated earnings, which were equal to the initial endowment, composed of the Part 1 fixed wage (1200¢), plus their gains and losses from buying the asset in previous periods.

To make the potential monetary loss associated with investing in the asset meaningful, we asked participants to invest the fixed wage they earned in Part 1 during the investment task. In addition, participants were given a loan of 1000¢ for liquidity reasons, which had to be repaid at the end of the experiment (as in Plott and Sunder, 1982, 1988).[5] If the current wealth of participants (including the loan) was no longer sufficient to repay the loan, they would go bankrupt.[6] In that case, participants were no longer able to purchase the asset and had to wait until the end of the session (while provided with Internet access). Investors who went bankrupt lost the fixed wage they earned in Part 1 and were only rewarded with a €5 show-up fee.[7]

Because participants could lose their entire endowment when facing very large losses, they might have believed that the experimenter was purposefully engineering the draws to ensure very large losses would occur, thus reducing participants' earnings and lowering the cost of the experiment. To make it clear to the participants that the sequence of draws was random and thus unpredictable, we adopted the following hand-run procedure. Before participants read the instructions, we showed them a transparent box containing 302 tokens of six different colors, each of which was associated with a potential return from the asset (blue = 10¢, red = 20¢, orange = 30¢, green = 40¢, purple = 50¢, yellow = −1000¢). There were 60 tokens of each color, except for the 2 yellow tokens.

[3] It is standard to use a large number of trials in research assessing the impact of electrodermal activity on behavior in stochastic environments (Bechara et al., 1997).

[4] This design implies that participants could not bid the exact expected value of 23.2. In any case, even if a participant had computed the exact expected value, the restriction to use integer bids (e.g., 23) would introduce only minor rounding noise and would not generate systematic overpricing. This effect is also common across treatments and therefore does not affect pairwise comparisons.

[5] This loan ensured that participants would have enough cash to bid for an asset even after a very large loss.

[6] Participants would typically go bankrupt if they suffered two very large losses.

[7] There is limited liability in our experiment because bankrupt participants did not repay their loans in full. On average, they repaid 73.8% of the loans.

Once everyone had seen the tokens, we told participants we were taking a picture of the box that would be displayed on their screens during the experiment.[8] By observing this picture during the experiment, participants could form an estimate of the frequency of occurrence of each token. The fact that the distribution of tokens was not fully known by participants allowed for learning during the experiment.

For the first 15 sessions we conducted (baseline physio of CCH), one participant was randomly selected to be the picker and escorted to a separate room. We asked the picker to put all the tokens in the transparent box into an opaque bag and draw tokens with replacements. The picker entered the token draws on a computer and on a separate sheet of paper in real time. The picker signed this sheet of paper upon completing the task; it was then shown to all other participants at the end of the experiment to ensure the credibility of the procedure. The picker did not know the instructions for the investment task, to avoid any cheating attempts or any retaliation by peers.[9] The picker was paid a fixed amount of €15 but incurred a €5 penalty if the task was not completed within one hour to ensure timely completion of the experiment.[10] During the task, one of the experimenters closely monitored the picker to ensure that the procedure was correctly followed. For all the other sessions, we explained that 15 participants known as pickers had been randomly selected in 15 previous experimental sessions. We carefully explained their role to participants. At the beginning of each of these later sessions, a participant was randomly selected to choose a number between 1 and 15 in order to select the sequence of draws from among the 15 previous experimental sessions.[11] For each treatment, we ensured that a sequence of draws could not be selected in more than one session, thus facilitating comparability across treatments.

2.2. Treatment conditions (baseline-feedback and market)

In addition to the baseline treatment described above, we implemented the baseline-feedback and market treatments. The aim of the former was to capture the potential effect of social information; participants observed the individual bids set by all the other investors in the group after they made their decision and before receiving any feedback regarding their earnings in a given period. The only feature that differed between the baseline and baseline-feedback treatments was the additional feedback screen displayed to participants.

In the market treatment, the same feedback screen containing information on others' bids as in the baseline-feedback treatment was displayed. The only difference between the market and baseline-feedback treatments was the pricing mechanism. To determine the price in the former, the uniform random draw over [1, 50] of the BDM mechanism was replaced by a uniform random draw over the bids set by the participants. Those with a bid strictly higher than the price bought the asset.[12] This is similar to a random n^{th}-price auction.[13,14] In our design, prices were similar in the market (Mean = 25.24¢, SD = 12.76¢), baseline (Mean = 25.80¢, SD = 14.24¢), and baseline-feedback (Mean = 25.54¢, SD = 14.28¢) treatments. The random n^{th}-price auction resembles a BDM mechanism because both the price and the number of buyers will vary across iterations. According to Shogren et al. (2001), truth-telling is the dominant strategy in a private value n^{th}-price auction, similarly to the BDM mechanism.[15]

The comparison between the baseline-feedback treatment and the market treatment intends to capture the impact of competition. Yet, we acknowledge that the market treatment changes both competition and the strategic environment because purchase probabilities depend endogenously on others' bids (whereas it is not the case in the baseline-feedback treatment). This introduces strategic uncertainty that is distinct from competition per se. A participant may bid higher in the market not because of emotional arousal but because of rational hedging against the risk that others bid high. However, standard models do not predict treatment differences, while prospect theory can partially explain results. Indeed, the market treatment is designed so that under expected utility theory, we expect no differences in bids across treatments. We confirm this claim using simulations of the time series of bids for the market and baseline

[8] Actually, a photograph of the box was taken prior to the first experimental session so that the picture displayed on participants' screens was exactly the same in all sessions.

[9] The other participants knew the picker did not know the instructions for the investment task. An English translation of the instructions for the picker is reported in Online Supplementary Material (OSM) I.2.

[10] This penalty was never implemented. After the picker started his or her task, one of the experimenters installed the physiological tool on the remaining participants (see Section 2.3) who then read the instructions for the investment task. Because the picker started his or her task before the investment task, the potential issue of the picker drawing tokens too slowly never occurred.

[11] The yellow token was actually drawn once in four sequences, twice in four sequences, thrice in three sequences, four times in three sequences and was never drawn in one sequence. The complete sequence of draws is available in Appendix A in CCH.

[12] This implies that nobody would buy the asset if all bids were the same in a given period. However, this never occurred in any of the 8,100 cases.

[13] The reason for not using the k^{th}-price auction for the market treatment (with the number of assets being sold at k-1) is to avoid making the number of assets being sold constant across periods. Note that the number of assets bought in the baseline treatments is not fixed. By picking one bid at random, we introduce randomness in the number of assets being sold, with the maximum number of sold assets being equal to the number of players in the market minus one and the minimum being zero.

[14] Although the market treatment was made as similar as possible to the baseline-feedback treatment, two adjustments were made with respect to the BDM mechanism used in the baseline and baseline-feedback treatments. First, the condition for a participant to buy into the lottery was conditional on setting a bid strictly higher than the selected price. Second, a participant could only enter a price between 1 and 50 (rather than between 0 and 50). This ensured that a participant could always decide not to participate in the auction by setting a price equal to one.

[15] Given the absence of communication and the high number of bidders, tacit collusion is very unlikely to be observed in our setup (for a discussion, see Potters and Suetens, 2013). We are not aware of any evidence of collusion in the auction setting considered here. Furthermore, collusion would go against our main hypothesis that bids are higher in the market treatment than in the baselines.

treatments for a broader range of model specifications. More specifically, we show no treatment differences in bidding behavior for the class of models studied in CCH, particularly the expected utility model and the prospect theory model with a fixed reference point in income; see online supplementary material (OSM) III. While prospect theory with elevated reference points can partially explain the bidding gap (see Section 5.7), the physiological response provides additional mechanism evidence: standard strategic explanations alone do not naturally predict heightened physiological arousal after winning bids. Moreover, predictability of bids increases over time in our design because of participants' increasing tendency to submit bids that are very close to their bids in the previous period, so that the impact of strategic uncertainty remains limited overall and will not be discussed further.

Our design is not a factorial one. It isolates competition conditional on social feedback by comparing the market and baseline-feedback treatments. We did not implement a market-without-feedback treatment because competition in actual markets inherently involves observing prices or bids generated by others. Moreover, removing feedback would substantially alter the strategic environment and reduce comparability with the benchmark market institution. Our study does not aim to isolate the effect of different levels of social feedback within a market, such as revealing or withholding the full distribution of bids. Rather, it focuses on the impact of moving from a non-market to a market institution where price-based feedback is inherently present.

An English translation of the instructions for the investment task for each of the three treatments is reported in OSM II.

2.3. Measurement of emotions

For our three treatments, we conducted some sessions during which participants played the investment task while physiological measures were recorded (baseline physio, baseline-feedback physio, and market physio treatments). This experimental design feature allowed us to precisely assess the emotional arousal (i.e., the magnitude of an emotional response) of participants using physiological tools measuring electrodermal activity during the investment task (Critchley et al., 2000; Boucsein, 2012; Christopoulos et al., 2019). This emotional arousal is a manifestation of the basic emotion of surprise (Ekman, 1992) and as such is deprived of positive or negative valence. The baseline physio data are those collected by CCH and serve as a benchmark, while the baseline-feedback physio and market physio data are collected for the purpose of studying the impact of emotions in a market context.

From a practical point of view, following CCH, one of the experimenters placed electrodes on the second phalanx (palmar surface) of the index and middle fingers of each participant's non-dominant hand using a Velcro strap and isotonic gel. Another experimenter checked the quality of the recordings before the experiment began. Setting up the physiological equipment took about 20 min on average.

In our setup, we recorded electrodermal responses to two types of stimuli :[16] (i) a decision is made (referred to as decision arousal),[17] and (ii) the earnings for the period are shown on the screen (referred to as feedback arousal). Because our focus is on the emotional arousal associated with buying or not buying the asset, we focus on feedback arousal in our analyses. To ensure that sufficient time elapsed between stimuli, we inserted a four-second waiting screen after a decision was made and after the receipt of end-of-period feedback. A timer on the screen indicated the time participants had to enter a price using a cursor.[18] If participants did not enter a price on the screen and validate that decision on time, the number indicated by the cursor was selected. To prompt participants to decide each period, the default value on the cursor was 50. Our metric of interest is the amplitude of the signal as computed using the Matlab routine developed in Joffily's (2018) electrodermal activity toolbox, which is equal to the peak of the physiological response measured in microsiemens.[19]

In the baseline-feedback physio sessions, to obtain a sense of the valence of the emotions involved, we included a post-experimental survey in which we asked participants about any emotions (anger, fear, joy, and sadness) they felt when they faced a financial asset that induced a 1000¢ loss (see OSM II.2) and a financial asset that delivered a 10¢ reward or a 50¢ reward (see OSM II.3).

[16] After a stimulus is observed, the electrodermal activity needs time to rise; this is referred to as latency and is about four seconds on average. In the seconds that follow, the signal rises until it reaches a peak. In the absence of further stimulation, the signal recovers its baseline (pre-stimulus) level.

[17] This relates to what Bechara et al. (1997) refer to as anticipatory arousal.

[18] Participants were required to make their decision within 10 s in each period (except in the first and second periods for which they had 30 s and 20 s, respectively), in order to ensure that they progressed through the experiment at a comparable pace and to avoid excessive waiting times that could otherwise affect physiological recordings.

[19] As explained in CCH and in contrast to Breaban and Noussair (2018) and Kunreuther and Pauly (2018), we did not use face-reading software or survey measures to elicit the valence of emotions during the investment task. Although clearly appealing in identifying emotions, face-reading techniques have been challenged by emotion scholars (e.g., Keltner and Cordaro, 2017; Barrett et al., 2019; Martinez, 2019; Pollack et al., 2019). Moreover, we sought to avoid having the elicitation of emotional valence interfere with participants' behavior in the investment task and our physiological recordings. Finally, eliciting emotional valence throughout the investment task would have extended an experiment that was already long.

2.4. Survey

In Part 1, we collected extensive individual information regarding risk, loss, and ambiguity attitudes, along with personality traits, cognitive skills and demographic data. We also elicited estimations of the percentage of yellow and orange tokens in the photograph of the box of tokens that was displayed on participants' screens during the investment task in Part 2. An English translation of the eight blocks of tests we performed is reported in OSM I.1.[20]

2.5. Protocol

Between November 2018 and October 2023, we invited a total of 560 participants from a participant pool of more than 2500 students at a major university in France; 44% of the participants were male, and their average age was 21.8 years old. All tasks were computerized; we conducted a total of 62 sessions (see Table 1).

Between November 2018 and June 2019, all sessions were conducted in the laboratory. For the baseline physio sessions, the two parts of the experiment took place on different days. To limit attrition, participants were only paid the show-up fee (€5) at the end of the first part and thus needed to come back on another day to collect their earnings, which consisted of a fixed wage of €12 and a small and variable amount of pay (either positive or negative) depending on their decisions in some of the tests, after completion of the repeated investment task. Part 1 lasted for an hour and Part 2 for 3.5 h. Average earnings were approximately €39. For the baseline, baseline-feedback, and market treatments, Part 1 was shortened, lasting half an hour and performed on the same day and during the same session as Part 2. Overall, these sessions lasted 3.5 h on average. Earnings were similar to the baseline physio sessions except that participants did not receive a second show-up fee for their presence on a second day.

Between April 2022 and October 2023, we ran new waves of baseline, baseline-feedback, and market physio experiments that we preregistered using AsPredicted (#144,573).[21] Part 1 was conducted online and made even shorter: about 20 min. Only participants who completed Part 1 online could participate in the lab experiment in Part 2. At the end of Part 2, we also added a questionnaire about self-assessment of emotions (as described in Section 2.3 above and presented in OSM II.2 and II.3) and a comprehension quiz for the BDM procedure (see OSM I.4). Part 2 lasted for three hours; earnings were similar to those of non-physio sessions.[22]

3. Hypotheses

In our design, comparisons across treatments allow us to study the two main features of the market institution: social feedback and competition. Based on the existing literature, we derive three pre-registered hypotheses regarding the impact of these dimensions on bidding behavior.[23]

3.1. Social feedback (Hypothesis 1)

Regarding the social feedback dimension, a rapidly growing number of experiments have shown evidence of peer effects in risk-taking in financial decisions.[24] Part of this literature focuses on rank incentives, which are non-monetary incentives related to one's relative position. For example, Kirchler et al. (2018) show that rank incentives increase risk-taking among underperforming professionals, but not among students, when people invest for themselves.[25] Corazzini and Greiner (2007) do not find any effect of others' information on sequential risky decisions, in line with the results with students in Kirchler et al. (2018). Lindner et al. (2021) extend the analysis of Kirchler et al. (2018) on rank incentives by separating the effects of self-image and status motives on risk-taking. They show that risk-taking among students is higher when the winner or the loser is publicly announced. However, they do not observe these effects in the case of professionals. Finally, they observe that underperforming investors take more risks than outperformers when rankings are displayed and the winner or loser is publicly announced. In the same vein, Kuziemko et al. (2014) show that individuals take more risks when they are at the very bottom of a performance ranking because of a phenomenon they refer to as "last-place aversion." Dijk et al. (2014) and Fafchamps et al. (2015) also find that underperformers take more risks to catch up with top performers. Schwerter (2024) finds that portfolio choices depend on a social reference point, such as another participant's income.

[20] In sessions implementing baseline, baseline-feedback and market treatments, we conducted tests of Blocks 1 to 8. In half of the baseline physio sessions, we conducted 12 blocks (see CCH). In baseline-feedback physio sessions, market physio sessions, and half of the baseline physio sessions, for Part 1 to be implementable online within a reasonable duration of 20 min, we conducted only the following tests: risk aversion in the gain domain (Block 2), estimation of tokens (Block 5), loss aversion (Block 8), availability heuristic 1 and 2 (Blocks 7 and 10), questions 5, 11, 17, 21, 23, 29 35, 41, 45, 47, 53, 59, 69, 93 of the personality test (Block 3), and demographic data (Block 12); we also added a gambling fallacy test (Block 13).

[21] Available at: https://aspredicted.org/6S7_8QR. Physiological experiments were not possible during COVID, which explains the temporal gap between experiments. Importantly, the experiments were conducted in the same lab with the same recruiting procedure targeting the same population.

[22] The baseline design of the experiment reported in this paper was approved by the IRB of INSERM (#18-493) in May 2018; the study was also approved by the local ethical committee.

[23] In the preregistration document, Hypothesis 1 encompasses Hypotheses 1 and 2, as described in this section. Preregistered Hypotheses 2 and 3 correspond to Hypotheses 3i and 3ii in this section.

[24] See Trautmann and Vieider (2012) for an overview of these effects in decisions under risk.

[25] Kirchler et al. (2020) show that the same result is obtained when they invest on behalf of third parties.

Table 1
Treatment sessions.

Treatment	Dates	Number of sessions	Number of participants	Composition of groups
Baseline	May–June 2019	6	70	9 groups of 6 4 groups of 4[1]
Baseline physio	November 2018–February 2019 April 2022	30	171	2 groups of 7 17 groups of 6 11 groups of 5
Baseline-feedback	May–June 2019	5	72	12 groups of 6
Baseline-feedback physio	September–October 2023	8	95	15 groups of 6, 1 group of 5[2]
Market	May–June 2019	4	71	11 groups of 6 1 group of 5
Market physio	May–December 2022	9	81	6 groups of 6 9 groups of 5

[1] The number of participants in each group was irrelevant in the two baseline treatments because only the information about one's own bids was shown on the screen.
[2] One session ($n = 12$) crashed in period 269, which is why we collected one more session than intended ($n = 95$ instead of 80).

They show that decision makers make less risk-averse choices when peers' earnings are high. Lahno and Serra-Garcia (2015) demonstrate that both social learning and income comparisons play an important role in understanding peer effects, where social learning occurs when one obtains critical information about the value of an investment by observing others' decisions.[26] In a portfolio choice experiment, Gortner and van der Weele (2019) find that peer information lowers within-group variation in peer earnings and increases diversification, thus reducing risk-taking. Beyond individual portfolio choices, Schoenberg and Haruvy (2012) study the impact of social information in an experimental asset market. They find that observing the earnings of the top performer increases the likelihood of bubbles.

Previous work has also used field data to assess peer effects in financial decisions such as stock market participation (Hong et al., 2004; Kaustia and Knüpfer, 2012) and trading decisions (Kelly and Gráda, 2000; Hong et al., 2005; Shive, 2009). For example, Simon and Heimer (2015) provide evidence that social interactions contribute to the use of active investment strategies. Using a high-stakes field experiment conducted with a brokerage firm, Bursztyn et al. (2014) study two different channels by which peer effects might operate: social learning and social utility, which is the utility one gets from holding the same asset as others. Both social learning and social utility channels are found to have statistically significant effects on investment decisions.

In our setup, the baseline-feedback treatment introduces social feedback by showing other traders' bids to all participants. This provides bidders with all the information they need to calculate and understand their payoffs in a given period. However, we purposefully left aside many of the ingredients that have been shown to trigger peer effects, such as ranking incentives, social interactions, and reputational concerns. These other types of social feedback might have increased participants' competitive drive, making it harder to isolate the distinct impact of the market treatment on competition and bidding behavior. We should thus note that in our design the two main channels for peer effects – social learning and social utility – are more limited than in previous studies (e.g., Gortner and van der Weele, 2019; Apesteguia et al., 2020).

That said, in line with the existing literature on peer effects and risk-taking, we expect feedback to promote rather than hinder risk-taking, thus leading to higher bids in the baseline-feedback than in the baseline treatment. We summarize this conjecture in Hypothesis 1.

Hypothesis 1. (Social feedback).

Bids in the baseline-feedback treatment will be higher than in the baseline treatment.

3.2. Competition

Beyond social feedback, the market treatment differs from the baseline one because of the presence of competition (Deutsch, 1949; Malhotra, 2010). In the market treatment, traders compete for the purchase of the asset in an auction, so not all bidders can buy the asset. It follows that if traders are unable to purchase the asset, that is because others have outbid them. By contrast, in the baseline and baseline-feedback treatments, all traders might be able to buy the asset in a given period if the random BDM number is low enough. In both baseline treatments, when traders fail to purchase the asset, they can attribute it to an unusually high random BDM number and not, unlike in the market treatment, to the bidding behavior of other traders.

In line with the competitive arousal hypothesis (Ku et al., 2005; Malhotra, 2010), we posit that competition will exacerbate emotional arousal associated with buying the asset and magnify the joy of winning (see Wells, 1924; Cox et al., 1988; Goeree et al., 2002; Cooper and Fang, 2008; van den Bos et al., 2008). Ku et al. (2005) emphasize that the desire to win is magnified in the presence of competition, thus leading to higher bids in the market treatment than in the two baseline treatments. We summarize this prediction as follows.

[26] Bault et al. (2011) and Frydman (2015) present similar results, along with neurological evidence.

Hypothesis 2. (Competition).

Bids in the market treatment will be higher than in the baseline and baseline-feedback treatments.

We note that the literature isolating the competition dimension of markets is scant; indeed, we could only identify two papers (Noussair et al., 2004; Mengel and Peeters, 2022) directly comparing a market mechanism with an individual investment task. Mengel and Peeters (2022) study the causal impact of markets on risk-taking by comparing a market treatment implemented using a call auction with a non-market treatment implemented using a BDM. In both treatments, people could trade two assets that varied in riskiness. When the bids and asks of other participants were displayed in both treatments, the study reports that the risk premium on the riskier asset was larger in the market than in the non-market treatment toward the end of the experiment. However, Mengel and Peeters (2022) use a complex environment with private information, uncertainty, and multiple assets, making it difficult to directly compare their setup with ours. Noussair et al. (2004) consider a simpler design that compares bidding behavior in a BDM with a second-price auction. They report that bids are higher in the auction than in the BDM and are also closer to the asset's expected value.

3.3. Emotions and financial decisions

Numerous studies have emphasized how emotions can alter expected utility calculations, as put forth by the proponents of the "risk-as-feelings" hypothesis (Loewenstein et al., 2001) and the "affect heuristic" (Slovic et al., 2007). In the finance literature, scholars have increasingly recognized the relevance of emotions in markets (Shefrin, 2007; Lo, 2017), showing that induced excitement can produce higher bids (Andrade et al., 2015).

In particular, the competitive arousal hypothesis posits that markets will produce "an adrenaline-laden emotion state that can arise during competitive interaction" (Malhotra, 2010, p. 140). The physiological arousal triggered by winning a competitive auction has long been recognized as illustrated by the *calor licitantis* ("bidder's heat"), which under Roman law, protected a bidder who had overpaid due to an abundance of excitement (Corpus Juris Civilis, D. 39,4,9 pr.; see Malmendier and Lee, 2011).

To provide a direct test of the competitive arousal hypothesis, we assess the impact of the market treatment on emotional arousal. In line with this hypothesis, we expect that emotional arousal associated with winning bids will be higher in the market than in the two baseline treatments, whereas no differences will be observed for non-winning bids (Hypothesis 3i). This hypothesis emphasizes the increase in physiological arousal associated with winning bids due to competition while positing no effect on non-winning bids. Although investors' arousal could also be magnified *a priori* when not winning an auction, previous research using physiological recordings in gambling tasks has shown limited arousal associated with losing (Coventry and Constable, 1999; Coventry and Hudson, 2001; Wulfert et al., 2005). In our case, not buying the asset does not result in monetary losses but rather a zero payoff, thus leaving investors' earnings unaffected and potentially further limiting any emotional reaction. This is because a prerequisite for any event to produce physiological arousal is triggering the basic emotion of surprise, which tends to be limited in the case of non-winning bids (Joffily and Coricelli, 2013). In addition to testing whether markets trigger emotional arousal due to winning (Hypothesis 3i), we examine in Hypothesis 3ii whether this heightened arousal can account for the higher bid levels in the market than in the two baseline treatments, as posited in Hypothesis 2. However, establishing this link is challenging due to endogeneity issues. Indeed, investors who place higher bids are more likely to submit winning bids, thus experiencing arousal more frequently, which in turn leads to even higher bids. To mitigate this issue, we study the impact of base rate arousal, as measured in the first five periods, on bidding behavior in subsequent periods. Because the effect of winning bids on emotional arousal is specific to the market treatment (Hypothesis 3i), we expect that bids will be higher in the market than in the baseline treatments for traders who exhibit a high base rate level of emotional arousal. By contrast, we posit that the arousing effect of winning bids will not be observed for people who exhibit a low base rate emotional response to bidding outcomes. We thus expect no treatment differences for these traders. We summarize our predictions regarding emotional arousal in Hypothesis 3.

Hypothesis 3. (Arousal and Markets)

(i) Emotional arousal will be higher in the market than in the baseline and baseline-feedback treatments for winning bids, but no differences will be observed for non-winning bids.

(ii) Bidders with a high base rate of emotional arousal will bid higher in the market than in the baseline and baseline-feedback treatments, whereas no treatment differences will be observed for those with a low base rate.

4. Results

As preregistered and in line with CCH, our model specification uses panel regressions with random effects and robust standard errors clustered at the session level, with and without all the individual controls collected for all treatments.

4.1. Hypotheses 1 and 2 (bids across treatments)

We first study the dynamics of bids across treatments and show that bids started at similar levels before diverging around period 100 (see Fig. 1). Even though our setup is one in which all periods are independent so that one cannot retrade the asset in future periods, all treatments exhibit hump-shaped dynamics, a common bubble-crash pattern often found in the experimental bubbles literature (Noussair and Tucker, 2013; Palan, 2013; Smith et al., 1988). In the market treatment, this bubble pattern is stronger than in the other two treatments. Bids start below the fundamental value before peaking in the middle of the experiment and crashing toward

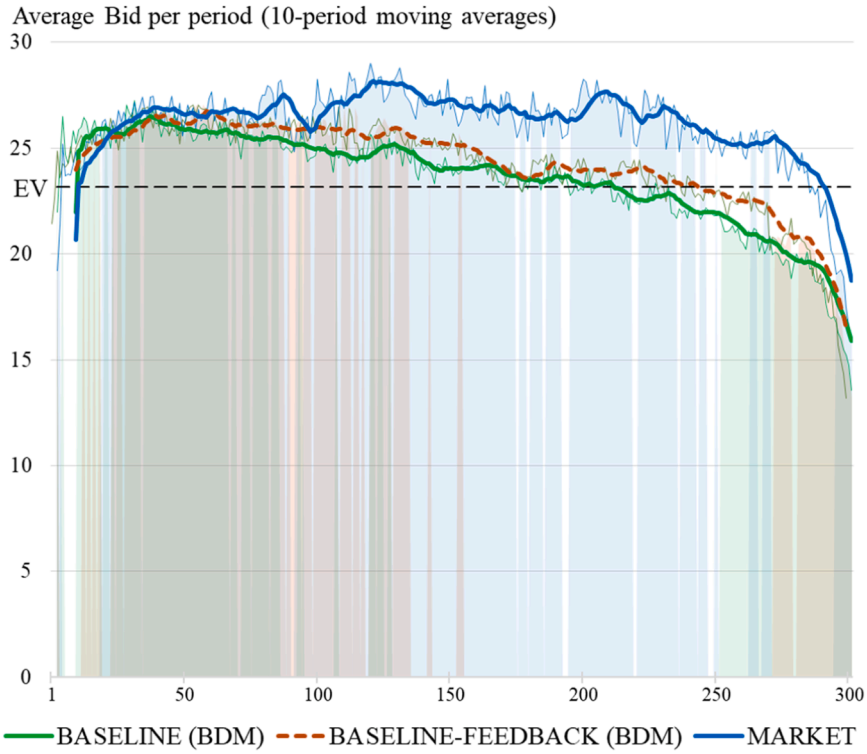


Fig. 1. Average bids per period along with 10-period moving averages (thick lines) across treatments.
Note: Thin lines show the average bid for a given period across all participants in a given treatment. Colored bands indicate when the bids in a given period and treatment deviate significantly (at a 1% significance level, sign rank tests) from the expected value (EV=23.2). Each color band corresponds to a different treatment. For example, a blue band between periods 200 and 210 indicates that, during these periods, bids in the market treatment were significantly higher than the expected value. Note that the EV of 23.2 is very close to the median bid prediction of 23.0 using model simulations from CCH (see OSM II). By construction, participants who went bankrupt could not post subsequent bids, so 5.6% of the bid data are missing. There were no significant differences in the proportion of bankruptcies across treatments (proportion tests: 12.9%, 16.8%, and 10.5% for baseline, baseline-feedback and market treatments, respectively. All pairwise comparisons report p-values greater than 0.1).

the end.[27] By contrast, bids start above the fundamental value, increase and then decline over time in the baseline and baseline-feedback treatments, with a decline that start much earlier than in the market treatment.

Overall, bids were 3.0% higher on average in baseline-feedback (Mean = 24.35¢, SD = 10.05¢) than in baseline (Mean = 23.63¢, SD = 10.62¢) but these differences were not statistically significant (see Fig. 1 and the non-significant variable Baseline-feedback in Table 2). This leads us to reject Hypothesis 1. Bids were 9.1% higher in the market treatment (Mean = 26.11¢, SD = 12.39¢) than in baseline and baseline-feedback combined (Mean = 23.93¢, SD = 10.40¢). In Table 2, we show that the difference in bids between market and baseline is significant (see Market). The difference between market and baseline-feedback does not reach significance in regressions (1), (2), or (3) (see coefficient tests: "Market = Baseline-feedback," lower part of the table) but is significant in regression (4). However, the increase in bids in the market treatment compared to both baseline and baseline-feedback treatments combined is significant (see Market = Baseline-combined in the lower part of Table 2). Since the strongest evidence emerges when comparing the market treatment to the two baseline treatments pooled together, while direct comparisons between market and baseline-feedback are directionally consistent but statistically less robust, we provide only weak evidence for Hypothesis 2.

In Fig. 1, we observe that market is the only treatment in which average bids per period are significantly above the expected value of the asset in the middle of the experiment, as shown by the blue bands in Periods 100 to 200. Overall, average bids in a given session were significantly above the expected value in 74.0% of the periods in the market treatment compared to 25.3% and 36.7% for baseline and baseline-feedback, respectively (proportion tests comparing market and each of the two baseline treatments, $p < 0.001$). These results stress that overbidding is exacerbated in the market treatment compared to the baseline.

To study dynamics, we fit bids using a quadratic trend in Table A1 (Appendix A.1). For all treatments, we find evidence of a bubble-

[27] The crash leads to bids that are significantly lower than the expected value in the very last periods (see Fig. 3). This could be explained by a series of factors. First, regret could lead investors to be especially cautious in the last periods as they will not have enough time to recover (Loomes and Sugden, 1982; Bleichrodt and Wakker, 2015). Second, investors may have achieved their target earnings for the experiment by the time they reach the last periods (Pokorny, 2008; Corgnet and Hernán-González, 2019). At that point, the risk of incurring a large loss might loom larger than might otherwise be expected.

Table 2
Bids and treatment effects. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level are in (1) and (2). In (3) and (4), autoregressive (AR(1)) errors are used, and no period variable and period fixed effects are included; (std) stands for standardized variables.

	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE	Bid			
Market	2.2844**	2.0292**	2.2581***	1.9930***
	(1.0273)	(0.9738)	(0.7610)	(0.7546)
Baseline-feedback	0.6398	0.3477	0.7063	0.4072
	(1.0462)	(1.0176)	(0.7367)	(0.7300)
Physio dummy	0.6430	0.3249	0.8249	0.5204
	(0.9496)	(0.9074)	(0.6409)	(0.6402)
Number of large losses up to $t-2$	0.3542	0.3742	−1.1492****	−1.1358****
	(0.2907)	(0.2923)	(0.0451)	(0.0451)
Asset payoff in $t-1$	0.0115****	0.0114****	0.0143****	0.0141****
	(0.0024)	(0.0024)	(0.0011)	(0.0011)
Large loss dummy in $t-1$	12.7159****	12.5760****	14.3144****	14.1659****
	(2.4410)	(2.4399)	(1.1522)	(1.1543)
Period	−0.0391****	−0.0392****		
	(0.0034)	(0.0034)		
Male dummy (std)		−0.8489***		−0.8860***
		(0.3224)		(0.3069)
Risk aversion (std)		−0.7811**		−0.7606**
		(0.3421)		(0.3140)
Loss aversion (std)		−0.7992**		−0.7990**
		(0.3855)		(0.3153)
Constant	24.1851****	24.5298****	24.1629****	24.4908****
	(1.0039)	(0.9763)	(0.6543)	(0.6522)
Coefficient tests				
Market = Baseline-feedback	0.1916	0.1645	0.0568	0.0483
Market = Baseline-combined	0.0450	0.0510	0.0050	0.0080
Lee bounds				
Market = Baseline	(2.271****, 2.683****)			
Market = Baseline-feedback	(1.597****, 1.923****)			
Market = Baseline-combined	(1.996****, 2.372****)			
R^2	0.0388	0.0538	0.0313	0.0459
Observations	157,318	156,291	157,318	156,291
Number of investors	560	556	560	556

*$p < 0.1$. Market (baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the market (baseline-feedback) treatment. Baseline-combined is a dummy variable taking a value of one if a person was assigned to one of the two baseline treatments. This test reports the result for the regression in which the only treatment dummy is baseline-combined. Number of large losses up to $t-2$ equals the number of times a participant faced an asset paying off a large loss up to period $t-2$. Large loss dummy in $t-1$ takes a value of one if a participant faced an asset paying off a large loss in the previous period. Risk aversion {loss aversion} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}. Estimates of lower and upper bounds following the procedure in Lee (2009) account for selection issues due to the missing bidding data of bankrupt participants (5.6% of the data). We used 1000 replications for the bootstrapped standard errors.
**** $p < 0.001$,
*** $p < 0.01$,
** $p < 0.05$,

crash quadratic trend given that "Period" ("Period^2") is positively (negatively) significant in each treatment taken separately; see regressions (1) to (3). As suggested in Fig. 1, while all treatments exhibit non-monotonic bid dynamics, the market treatment displays substantially larger and more persistent deviations from fundamental value. The anatomy of the bubble-crash pattern is thus more pronounced for market than for the two baseline treatments (see quadratic trend features at the bottom of the table). Indeed, given the estimated quadratic trends for each treatment, a peak value of 25.76 (26.18) [27.85] is achieved in period 67 (96) [133] in baseline, baseline-feedback and market treatments, respectively. At its peak, overpricing was thus equal to 20.1% of the expected value of the asset in the market treatment, compared to 11.2% and 13.0% in the baseline and baseline-feedback. These results indicate that the amplitude of the bubble is more pronounced in the market treatment than in the two baselines.[28]

Result 1. (Bids, bubbles, and competition)

(i) Bids were significantly higher in the market than in the two baseline treatments.
(ii) Bids exhibited a more pronounced bubble pattern in the market than in the two baseline treatments.

[28] See Appendix A.5 for additional analyses regarding mispricing.

4.2. Hypothesis 3 (emotional markets)

As outlined in Hypothesis 3, one explanation involves emotional arousal, with higher bids being particularly rewarding to investors in markets, in line with the competitive arousal hypothesis, which suggests that rivalry and the joy of winning drive bidders to increase their bids. The joy of winning is also a central explanation of overbidding in the contest literature (Cooper and Fang, 2008).

Our work allows us to provide a quantitative physiological measure of competitive arousal by comparing the difference in physiological arousal across treatments when buying an asset. To assess our third hypothesis, we leverage a unique dataset of 347 participants in 300 periods across three treatments, amounting to 195,420 physiological recordings.[29]

4.2.1. Hypothesis 3i (arousal and joy of winning in markets)

We begin our study of the role of emotions by testing Hypothesis 3i, according to which winning bids that lead to buying the asset will trigger emotional arousal that will be more pronounced in the market than in the two baseline treatments. In Fig. 2, we show that emotional arousal is consistently higher after a winning bid in the market but not in the two baseline treatments. In the market treatment, investors showed an emotional reaction to winning bids in an average of 27.8% of cases, compared to 20.2% for all other bids. For baseline [baseline-feedback], the difference in emotional reaction was less pronounced (23.3%vs. 21.8%) [25.0%vs. 20.9%].

In Table 3, we show that these differences in emotional reaction to winning bids were significantly higher in the market than in the baseline treatment. This is the case because the coefficient for "Market × Win" is positive and significant across all specifications. In contrast, the coefficient for "Baseline-feedback × Win" is positive but not significant and about 10 times smaller than the coefficient for "Market × Win." The higher emotional reaction due to winning in the market treatment than in the baseline-feedback treatment is significant in all regressions (see the coefficient tests "Market × Win = Baseline-feedback × Win" in the lower part of the table). By contrast, the Market and Baseline-feedback variables are not significant, thus showing that no differences in arousal exist for non-winning bids between these two treatments and the baseline. Furthermore, the coefficient test for "Market = Baseline-feedback" cannot be rejected, so there is no significant difference in arousal between these two treatments for non-winning bids.

A visual inspection of Fig. 2 suggests that, in the first 40 periods, there is also an increase in arousal in the baseline-feedback treatment when investors bought the asset than when they did not buy the asset. To check for this possibility, we replicated the regressions in Table 3 for the first 40 periods (see Table A2 in Appendix A.2). As in Table 3, "Market × Win" is positive and significant across all specifications. Unlike Table 3, however, the coefficient for "Baseline-feedback × Win" now also reaches significance, though it is roughly half the size of the "Market × Win" coefficient. The difference between these two interaction effects is now statistically insignificant at conventional levels, as shown by the corresponding coefficient test in the lower part of the tables. These results are consistent with the observation that arousal levels are generally elevated in the early periods (see Fig. 2), when the excitement associated with winning is also particularly pronounced. Importantly, however, the early excitement related to winning, observed in the baseline-feedback treatment, vanishes over time. No such decay is observed in the market treatment, suggesting that the arousal response to winning is more robust in that case.

Because the arousal dummy variable is a binary one, the standard panel approach adopted in Table 3 turns into a linear probability model. Table A3 in Appendix A.2 shows that our main result, that is the higher emotional reaction due to winning in the market treatment than in the baseline-feedback treatment, is robust to using a panel probit regression.

In our analysis, endogeneity issues could arise because winning bids are more likely to be set by aggressive bidders ($\rho = 0.395$ between "Bid" and "Win", $p < 0.001$). We address endogeneity issues by controlling for bids in our regressions because "Win" is an exogenous variable conditional on bids. Alternatively, we could treat endogeneity issues in bids using observed prices as in CCH. In baseline and baseline-feedback, prices are determined using a BDM mechanism and are thus orthogonal to bids. In the market treatment, prices are determined by an auction and are thus a function of bids in a given period, so it is unsurprising that individual bids correlate positively with prices ($\rho = 0.326$, $p < 0.001$). To mitigate this issue, we can construct an alternative variable "Price$^{\perp}$" that is orthogonal to bids regardless of treatment.[31] This variable is thus uncorrelated with bids while correlating significantly with "Win" ($\rho = 0.687$, $p < 0.001$). In Table A4 in Appendix A.2, we use this variable as an instrument for "Win" and replicate our findings.

Our findings are consistent with Hypothesis 3i and more generally with the conjecture that the joy of winning is exacerbated in the market treatment. We examine our hypothesis in greater detail by inquiring about the valence of emotion, thus complementing our physiological arousal measure.

In Table 3, we excluded the 0.8% of observations associated with negative payoffs[32] because these large negative payoffs trigger a specific emotional reaction that is unrelated to competitive arousal and was studied in CCH for the baseline case.[33] CCH showed that arousal was linked to anger when investors bought an asset, and the payoff was −1000. Unsurprisingly, using data collected for

[29] This includes two recordings per period: decision arousal and feedback arousal. Absent bankruptcies and the two cases of deficient electrodes, we would have 208,200 recordings.

[31] We construct this variable using the orthog command in Stata 17.0. This command uses the Gram-Schmidt procedure (Golub and Van Loan, 2013) to transform a set of correlated variables into new variables that are mutually orthogonal. The resulting variables are uncorrelated thus eliminating multicollinearity issues and improving the numerical stability of the estimation.

[32] Unsurprisingly, because these observations constitute a small fraction of the data, our results are largely unaltered when including these periods in the analysis.

[33] Not only is the valence of the emotion different, as explained in the text, but that is also the case for the magnitude of the response. The average for arousal dummy was 56.6%, compared to 22.7% for the other payoffs with no major differences across treatments.

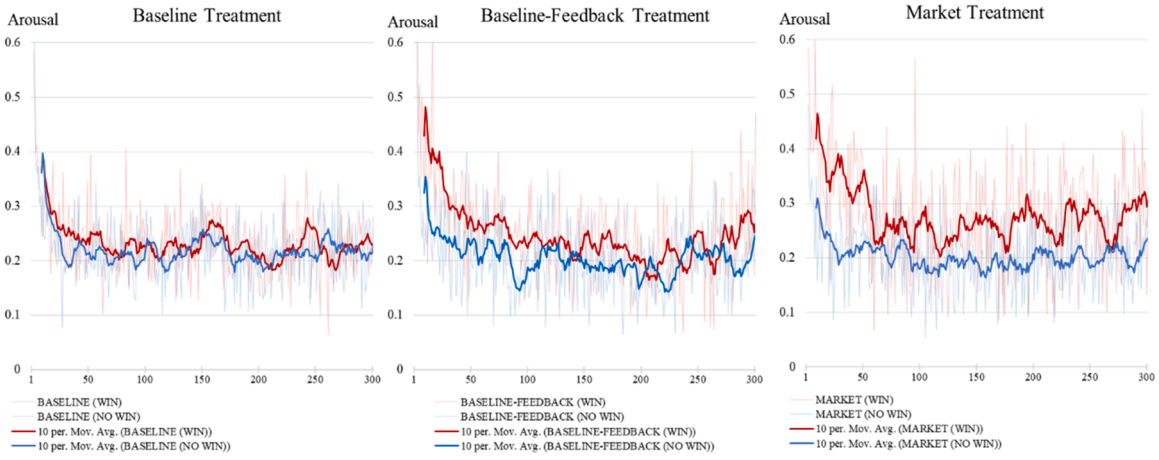


Fig. 2. Proportion of investors who showed emotional arousal after observing feedback in a given period and across treatments.
Note: Red (blue) curves correspond to cases in which the investor bought (did not buy) the asset. We show the periods in which the payoff of the asset was positive (99.2% of the data).[301]

baseline-feedback, we found that people did not report an anger response when buying an asset when payoffs were positive (see Table A5 in Appendix A.2).[34]

Of the four basic valenced emotions —fear, anger, joy, and sadness (Ekman, 1992)— only joy was reported as a prominent emotion in buying the asset and when the payoff was equal to its maximum possible value of 50.[35] In that case, participants reported feeling joy "very much" and anger, fear, and sadness "not at all." The joy emotion was thus more intense when buying the asset than any of the other emotions (sign rank tests; $p < 0.001$ in all cases). When not buying the asset, all reported emotions were of low intensity and significantly lower than the midpoint of the Likert scale. Still, sadness was the most intense emotion (sign rank tests; $p < 0.001$ in all cases), suggesting a "pain of losing" effect associated with non-winning bids that is the counterpart of the joy of winning. However, the pain of losing effect was of lower magnitude than the joy of winning (sign rank test for the difference in difference, $p < 0.001$). Overall, people reported being more joyful and less sad after a winning bid than after a non-winning bid. Interestingly, the self-reported emotional intensity associated with the end-of-experiment questionnaire was in line overall with physiological arousal (see Fig. A.1 in Appendix A.2).

A payoff of 50 means that winning bids cannot be associated with monetary loss, given that the maximum bid is 50. By contrast, most of the time (65.1%) winning bids were associated with a monetary loss when the asset payoff was equal to the minimum possible value of 10. In that case, we expect mixed feelings because the joy of winning is diminished by the pain associated with losing money. In line with that claim, participants reported low-intensity emotions that were significantly below moderate whether they had placed a winning or a non-winning bid (sign rank tests; $p < 0.001$ in all cases; see right panel of Table A5 in Appendix A.2). In contrast with the case in which the asset payoff was 50, sadness (joy) was more (less) pronounced after a winning (non-winning) bid when the payoff was 10 (sign rank tests; $p < 0.001$ in all cases). We refer to this effect as the "pain of winning." However, the impact of the pain of winning in our results should not be overstated. First, the joy of winning effect is of significantly higher magnitude than the pain of winning (sign rank test for the difference in difference; $p < 0.001$). Second, although winning bids were usually (65.1%) associated with a monetary loss when the asset payoff was 10, they were mostly associated with monetary gains in general (76.4%).

Fig. A2 in Appendix A.2 shows that arousal was higher in the market than in the two baseline treatments when asset payoffs were high (40 or 50), while that was not necessarily the case for low payoffs (10 or 20). Table A6 in Appendix A.2 shows that the increase in arousal in the market treatment is increased for high asset payoffs (40 or 50) compared to low asset payoffs (10 or 20), as shown by the positive and significant interaction term for "Market × Win × High payoff." Beyond the pure joy of winning, the increase in arousal in the market treatment after winning bids thus also captures what could be called the "joy of money," which could reflect heightened greed in markets (Seuntjens et al., 2014, 2015). This is confirmed in Table A7 (Appendix A.2), which shows that the term "Treatment Market × Win × Payoff" is consistently positive and significant.

One could ask if there is a joy of winning at all beyond the joy of money. Table A6 shows that low payoffs, defined as below the median payoff of 30, lead to winning bid arousal in the market treatment because the coefficient on "Market × Win" is positive and significant. This occurs even though investors suffer monetary losses in just under half the cases (49.0%) for low payoffs, compared to only 0.7% for high payoffs of 40 or 50. Yet, one notices that in the market treatment the coefficient for the impact of winning bids with high payoffs is two times higher than under low payoffs (coefficient tests: "Market × Win × High Payoff + Market × Win" = Market ×

[34] We study arousal as a function of payoffs rather than monetary gains and losses because the latter are endogenous since they depend on participants' bids.

[35] The only non-valenced basic emotion is surprise. Surprise tends to accompany the other emotions and is captured with our physiological measurement.

Table 3
Arousal and winning bids. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level are in (1) and (2). In (3) and (4), autoregressive (AR(1)) errors are used, and no period variable and period fixed effects are included. Negative payoffs periods are excluded from the analysis (99.2% of the data are included); (std) stands for standardized variables.

DEPENDENT VARIABLE	(1) Arousal Dummy	(2)	(3)	(4)
Market × Win	0.0453****	0.0450****	0.0458****	0.0453****
	(0.0099)	(0.0100)	(0.0068)	(0.0068)
Market	0.0003	−0.0005	0.0003	−0.0008
	(0.0192)	(0.0178)	(0.0188)	(0.0187)
Baseline-feedback × Win	0.0108	0.0105	0.0095	0.0092
	(0.0085)	(0.0086)	(0.0063)	(0.0063)
Baseline-feedback	0.0030	−0.0005	0.0041	0.0007
	(0.0194)	(0.0191)	(0.0179)	(0.0179)
Win	0.0210****	0.0211****	0.0216****	0.0218****
	(0.0044)	(0.0045)	(0.0039)	(0.0039)
Bid	0.0013****	0.0013****	0.0014****	0.0014****
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of large losses up to $t-2$	0.0107	0.0114*	−0.0025	−0.0022
	(0.0066)	(0.0066)	(0.0016)	(0.0017)
Asset payoff	0.0004****	0.0004****	0.0005****	0.0005****
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Asset payoff in $t-1$	0.0001	0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Large loss dummy in $t-1$	0.0707	0.0593	0.0303	0.0205
	(0.1009)	(0.1019)	(0.0953)	(0.0958)
Period	−0.0003**	−0.0003**		
	(0.0001)	(0.0001)		
Male dummy (std)		0.0248***		0.0249****
		(0.0077)		(0.0076)
Risk aversion (std)		0.0078		0.0085
		(0.0062)		(0.0073)
Loss aversion (std)		0.0017		0.0014
		(0.0090)		(0.0074)
Constant	0.3108****	0.3107****	0.1638****	0.1643****
	(0.0254)	(0.0254)	(0.0122)	(0.0122)
Coefficient tests				
Market × Win =Baseline−feedback × Win	0.0029	0.0032	< 0.001	< 0.001
Market = Baseline-feedback	0.9015	0.9980	0.8547	0.9460
R^2	0.0083	0.0112	0.0026	0.0054
Observations	96,264	95,243	96,264	95,243
Number of investors	344	340	344	340

Market (baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the market (baseline-feedback) treatment. Win is a dummy that takes a value of one if a participant bought the asset in a given period. Number of large losses up to $t-2$ equals the number of times a participant faced an asset paying off a large loss up to period $t-2$. Large loss dummy in $t-1$ takes a value of one if a participant faced an asset paying off a large loss in the previous period. Risk aversion {Loss} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}.

**** $p < 0.001$,
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Win"; $p < 0.05$ for all regressions). However, Table A8 shows that there is an emotional reaction due to winning bids in the absence of monetary gains, which is captured by the interaction term "Market × Win" being positive and significant. The share of the increase in emotional arousal that is captured by the joy of winning rather than by the joy of money can be estimated as

$$\frac{\text{'Market} \times \text{Win'}}{\text{'Market} \times \text{Win'} + \text{'Market} \times \text{Win} \times \text{Money Gain''}}$$

which ranges between 53.6% and 57.5% in the regressions in Table A8.

Result 2 summarizes our findings regarding our test of Hypothesis 3i.

Result 2. (Arousal across treatments)

(i) Investors were substantially more aroused after winning bids in the market than in the two baseline treatments.
(ii) No treatment differences in arousal were observed after non-winning bids.
(iii) The arousal associated with winning bids can only be partly attributed to monetary gains.

4.2.2. Hypothesis 3ii (base rate arousal)

We proceed to test Hypothesis 3ii, according to which bids are higher in the market than in the two baseline treatments, due to an increased level of arousal in this treatment. Our approach consists in testing one critical implication of our suggested emotional mechanism. In the absence of emotional arousal, traders' bidding behavior should not differ across treatments, because any observed differences would be due to the heightened arousal associated with winning bids in the market treatment. To study the impact of shutting off emotional arousal, which we manipulate only indirectly in the experiment through trading institutions, we use observed individual differences in base rate arousal. To isolate participants with low base rate arousal from those with high base rate arousal, we use a measure of base rate arousal defined as the number of times a person was aroused (Arousal dummy equals one) in the first five periods of each session, following the definition in CCH.[36] An investor is then classified as having low (high) base rate arousal when its level is below (above) the median of two. By definition, base rate arousal could be affected by the history of payoffs during the first five periods and by the treatments themselves. However, the mean payoff in the first five periods is uncorrelated with base rate arousal ($\rho = -0.014$, $p = 0.788$). Furthermore, we observe only small differences in base rate levels across treatments. The market treatment actually shows a slightly lower base rate arousal (39.5%) than the baseline (46.9%) and baseline-feedback (47.7%) treatments, although no significant differences emerge (rank sum tests; $p = 0.073$, 0.058, and 0.830 when comparing market and baseline, market and baseline-feedback, and the two baselines, respectively). Arousal in the first five periods is largely unrelated to payoffs and treatments because the base rate of arousal is primarily driven by novelty, which peaks when participants discover the experimental setup. Indeed, the rate of arousal is twice as high in the first five periods than in subsequent periods (45.3%vs. 22.6%, rank sum test; $p < 0.001$). To further validate the use of individual differences in base rate arousal, we examine whether participants with low and high base rate arousal are comparable on the basic control variables identified as potential drivers of bidding behavior. Therefore, any differences in bidding behavior between these groups are likely attributable to differences in emotional responses.

As expected, investors with high base rate arousal exhibited more frequent emotional responses to winning bids in subsequent periods than those with a low base rate (35.0%vs. 15.8%, rank sum test; $p < 0.001$). Furthermore, as expected, investors with high base rate arousal showed more frequent emotional responses to subsequent winning bids in the market (44.1%) than in the baseline (32.3%, rank sum test; $p = 0.006$) and baseline-feedback treatments (33.7%, rank sum test; $p = 0.038$). No arousal differences due to winning bids were observed for investors with a low base rate between market and baseline [baseline-feedback] (18.7%vs. 14.7%, rank sum test; $p = 0.199$) [18.7%vs. 14.5%, rank sum test; $p = 0.299$].

In line with Hypothesis 3ii, we observe that investors who had a low level of base rate arousal, defined as below the median of two, exhibited limited differences in bidding behavior across treatments (see left panel in Fig. 3). By contrast, we observe treatment differences for investors who had a high level of base rate arousal, defined as being above the median (see right panel in Fig. 3).

In Tables A9 and A10, we replicate the regression analyses in Table 2 for investors with low and high base rate arousal, respectively. In line with Fig. 3, we find that a significant increase in bids in the market treatment compared to the baseline only emerges for investors with a high base rate arousal (see "Market" in Table A10). This finding is consistent with Hypothesis 3ii and is summarized in Result 3.

As shown in Fig. 3, bids in the baseline-feedback treatment for investors with high base rate arousal are between the baseline and market treatments. In fact, baseline-feedback bids are significantly higher than baseline bids in regressions (1) and (3) while not being significantly lower than market in any of the regressions (see "Baseline-feedback" in Table A10). This suggests that feedback about others' bids might have also increased the joy of winning for investors with a high base-rate arousal level, leading them to increase their bids.

Result 3. (Bids and base rate arousal)

(i) Bids were not significantly different across treatments for those who exhibited low base rate arousal.

(ii) Bids were significantly higher in the market than in the baseline treatment for investors who exhibited a high base rate arousal but not significantly higher in the market than in the baseline-feedback treatment.

4.2.3. Exploratory analysis: earnings and bankruptcy rates

We have already shown that the market treatment tends to produce higher bids than the two baseline treatments, especially for those investors with a high level of base rate arousal. This implies that average bids are also higher than the expected value of the asset in the market treatment for investors with a high base rate arousal level. Because placing bids that are equal to the expected value would maximize one's expected earnings in all three treatments, it follows that investors with a high base rate arousal level will earn less in the market than in the baseline and baseline-feedback treatments (see Fig. 4, upper panel).

Higher bids in the market treatment were also associated with a higher risk of incurring a large negative payoff during the experiment, as participants were more likely to buy the underlying asset and thus suffer a large loss if the yellow token was drawn. In particular, when investors bought the asset twice in sessions in which it delivered a large negative payoff, they could go bankrupt. We therefore focus on sessions with two yellow draws, in which bankruptcy was possible for investors who bought the asset each time a yellow token was drawn; these sessions comprise 68.9% of the data. In these sessions, we observe that among investors with high base rate arousal, the frequency of bankruptcy was higher in the market treatment (31.3%) than in the baseline (14.0%) and baseline-

[36] The cited authors use a five-period cutoff because the first negative payoff across all series employed in their experiment occurs in period 7. This means the base rate arousal measure is not impacted by negative payoffs events, which we know from CCH produce a substantially higher level of arousal than normal positive payoffs.

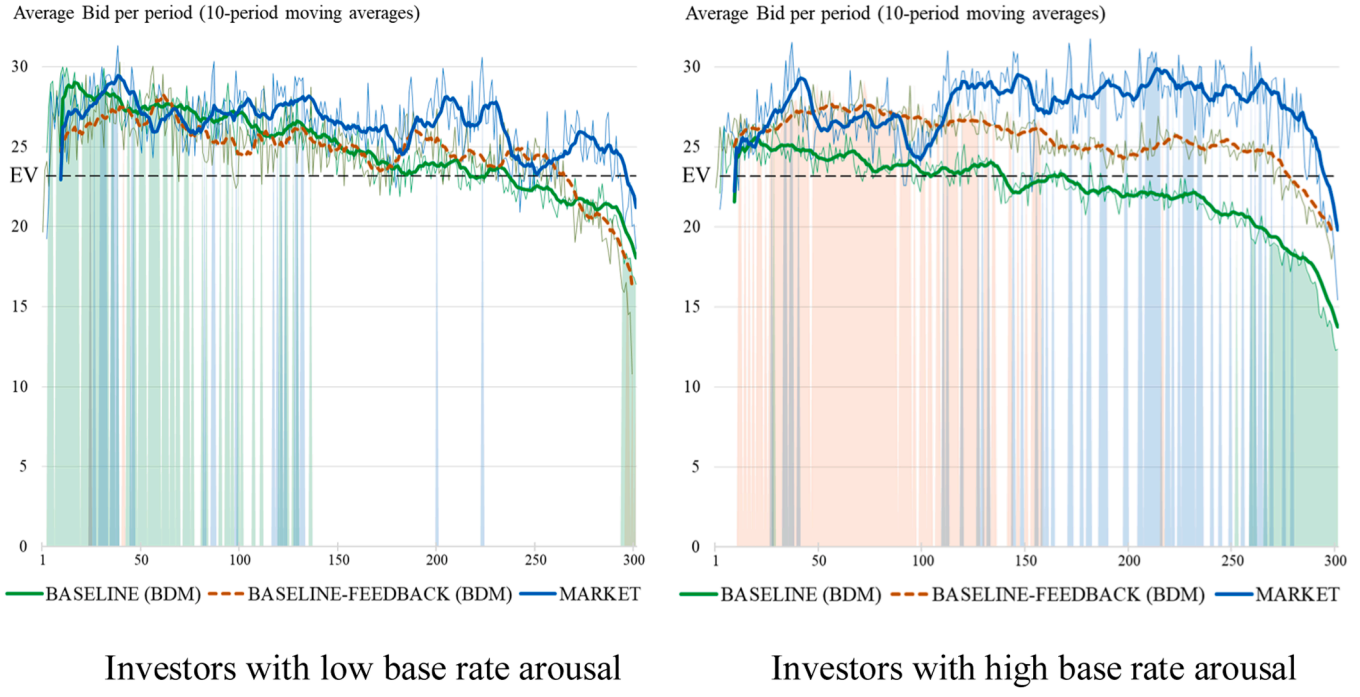


Fig. 3. Average bids per period and 10-period moving averages (thick lines) across treatments. *Left panel.* Investors who had a level of base rate arousal below the median. *Right panel.* Investors who had a level of base rate arousal above the median.

Note: Thin lines show the average bid for a given period across all participants in a given treatment. Colored bands indicate when the bids in a given period and treatment deviate significantly (at a 1% significance level, sign rank tests) from the expected value (EV=23.2). Each color band corresponds to a different treatment. For example, a blue band between periods 295 and 300 indicates that, during these periods, bids in the baseline treatment were significantly lower than the expected value. By construction, participants who went bankrupt could not post subsequent bids, so 4.4% (6.9%) of the bid data are missing for low (high) base rate arousal investors. There were no significant differences in the proportion of bankruptcies across treatments for low base rate and for high base rate arousal investors except for the comparison between baseline and market for low base rate investors (proportion test, $p = 0.048$).

feedback (23.3%) treatments (see Fig. 4, lower panel). By contrast, for investors with low base rate arousal, the pattern is reversed, with a higher frequency of bankruptcy in the baseline (25.6%) than in the baseline-feedback (14.3%) and market (0%) treatments. This suggests that low base rate arousal is particularly effective at protecting investors from bankruptcy in a market setting.

We show the statistical significance of these differences in Tables A11 and A12 in Appendix A.3. In Table A11, we report that the interaction term "Market × Base rate arousal" is negative and significant for regressions (3) and (4), showing that base rate arousal hurts participants earnings more in the market than in the baseline treatment. These regressions consider sessions in which bankruptcies were possible, which are characterized by the occurrence of at least two negative payoffs. The interaction term "Baseline-feedback × Base rate arousal" does not reach statistical significance; thus, base rate arousal is not detrimental in the baseline-feedback treatment when compared to the baseline. Although the magnitude of the coefficient for "Market × Base rate arousal" is about two to three times larger than "Baseline-feedback × Base rate arousal," depending on the regression, we report no significant differences between these two interaction terms (see coefficient tests at the bottom of Table A11). In the market treatment, the estimates in Table A11 show that for an investor with a median level of base rate arousal (equal to two), the decrease in earnings ranges from €3.29 to €5.58 for a three-hour experiment, which corresponds to about 10% of their earnings for the experimental session.[38]

Table A12 shows that similar results were obtained when considering bankruptcy rates; thus, base rate arousal was associated with more frequent bankruptcies in the market than in the baseline treatment (see "Market × Base rate arousal"). Furthermore, the coefficient test comparison between "Market × Base rate arousal" and "Baseline-feedback × Base rate arousal" is significant in sessions where bankruptcies were possible (see coefficient tests at the bottom of Table A12 for regressions (3) and (4)). This shows that, in terms of bankruptcies, base rate arousal was also more detrimental to traders in the market than in the baseline-feedback treatment.

Result 4 summarizes our findings regarding earnings and bankruptcies.

Result 4. (exploratory). (Bankruptcy, earnings and arousal)

In the market treatment, investors with high base rate arousal were more likely to go bankrupt and earned less in sessions where bankruptcy was possible than those with low base rate arousal. No differences between these two groups were observed for the baseline and baseline-feedback treatments.

Our final exploratory result on earnings and bankruptcy should be interpreted with caution. The literature following the somatic marker hypothesis has shown that emotions can also help investors anticipate and gauge financial risks, thus leading to better decisions and higher earnings (Damasio, 1996; Bechara et al., 1997; Bechara and Damasio, 2005). In particular, recent research using experimental markets has shown that anticipatory arousal, possibly reflecting fear and anxiety, is associated with higher earnings because it helps investors avoid excessive risk (Bossaerts et al., 2023; Corgnet et al., 2020).

In contrast to this literature, our analysis focused on the joy of winning, which was captured by assessing physiological arousal after observing payoffs (i.e., feedback arousal) rather than at the time of making a decision (i.e., decision arousal). In our study, there were no significant differences in decision arousal across treatments (see Fig. IV.1 and Table IV.1 in OSM IV), even when considering the interaction term between treatment dummies and winning bids in the previous period (Table IV.2 in OSM IV). It follows that the increase in bids in the market treatment compared to the baseline and baseline-feedback treatments cannot be accounted for by decision arousal.

An interesting avenue for future research would be to identify the institutional features under which anticipatory and feedback arousal can lead to different outcomes. Interestingly, our study suggests that in the absence of a market institution, any effect of emotional arousal on bidding behavior is more likely to be driven by anticipatory than feedback arousal. This follows from the fact that feedback arousal resulting from winning bids was limited in the baseline and baseline-feedback treatments.

5. Discussion of alternative mechanisms

We briefly review potential explanations for our findings that depart from the competitive arousal hypothesis.

5.1. Learning

The market treatment leading to exacerbated emotional arousal might have precluded learning and thus led to overbidding. This could have been the case as long as excitement was associated with heightened levels of stress, which has been shown to impair cognitive ability (Shields et al., 2016). However, we believe that learning plays a limited role in our 300-period experiment.

In the survey conducted before the experiment, we elicited investors' estimates of the percentages of orange and yellow tokens in the box used for the investment task. The median estimate for the orange [yellow] tokens was 18.2% [2.0%], compared to the actual value of 19.9% [0.67%] (sign rank test; $p = 0.006$) [$p < 0.001$]. This implies that 71.8% of the investors overestimated the probability of the occurrence of a large loss, thus underestimating the expected value of the asset. It follows that if the market treatment had indeed slowed down learning, bids should have remained at low values for a longer duration in that treatment. We observe the exact opposite; bids increased sharply in the early periods, especially in the market treatment (see Fig. 1).

The fact that overbidding persists across 300 periods also limits the potential role of learning. It follows that initial biases or misunderstandings, such as the underestimation of the cost of high bids in second-price auctions (Kagel et al., 1987; Georganas et al.,

[38] This decrease in earnings in the market treatment for a base rate arousal equal to two is calculated as follows: 2 × "Base rate arousal" + 2 × "Market × Base rate arousal", which leads to estimates of −3.29, −3.36, −5.58, and −5.42 in regressions (1) to (4), respectively.

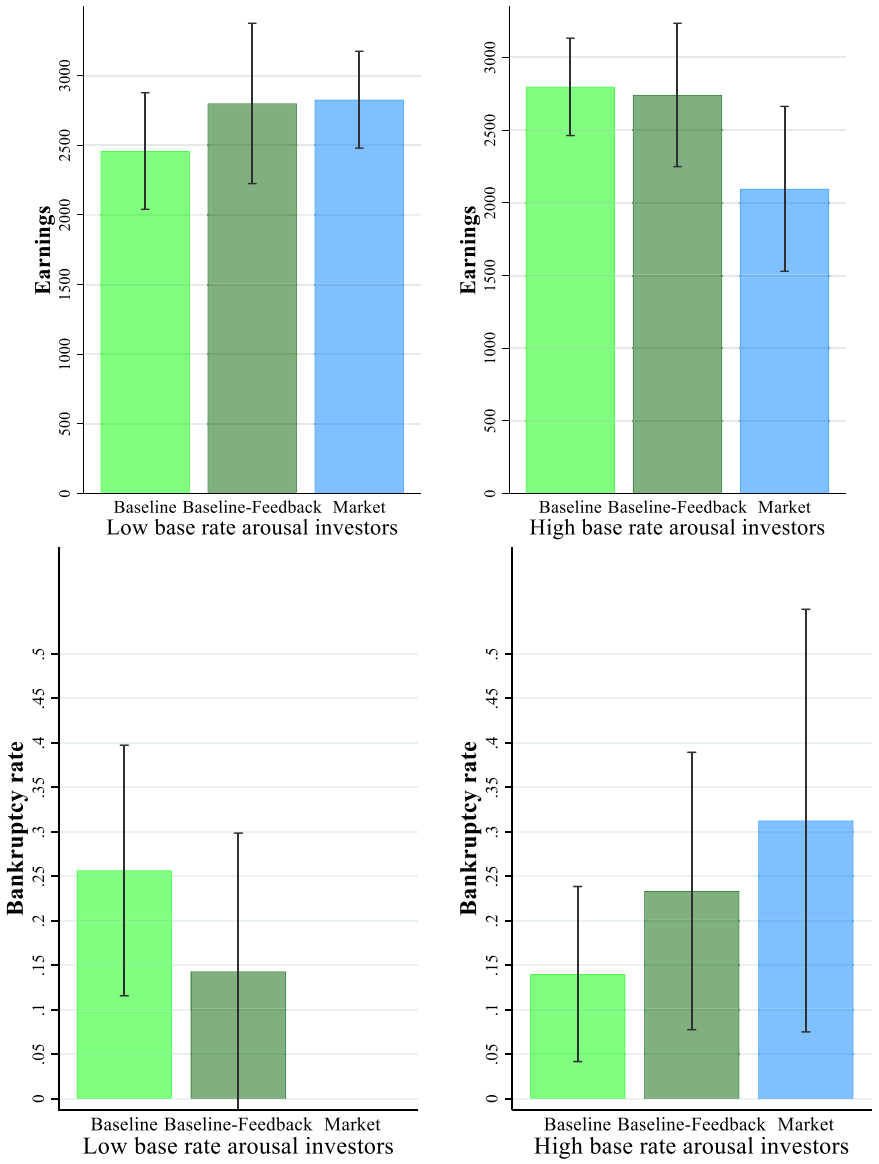


Fig. 4. Average earnings (bankruptcy rates) across treatments for low (high) base rate arousal investors in the left (right) panel for sessions in which bankruptcies were possible.[371] Note: 95% confidence intervals included for earnings but not for bankruptcy rates, which are simple proportions.

2017), should diminish over time.

Additionally, overbidding is observed even among investors with high cognitive ability, as measured by the Cognitive Reflection Test (see our survey in OSM I.1), a strong predictor of bias avoidance (Oechssler et al., 2009; Toplak et al., 2011; Meyer et al., 2024). While investors scoring above the median on the test made lower bids (with an average bid of 21.37¢ and a median bid of 22.0¢) than those below the median (22.66¢ and 23.0¢, respectively), their bids in the market treatment remained higher (22.66¢ and 25.0¢) compared to the baseline-feedback (20.33¢ and 21.0¢) and baseline (21.30¢ and 21.0¢) treatments (rank sum tests; $p < 0.001$).[39]

5.2. *Anticipated emotions*

Our interpretation of the competitive arousal hypothesis has been that the arousal experienced following winning bids leads investors to increase subsequent bids. However, an alternative view posits that anticipated emotions play a critical role in explaining bidding behavior (Engelbrecht-Wiggans and Katok, 2006, 2008; Delgado et al., 2008). Our design did not aim at isolating the specific

[39] Similar results are obtained when focusing on the top 10% of investors in terms of cognitive reflection.

role of anticipated emotions. However, our findings shed some light on the interaction between anticipated and experienced emotions. In particular, Fig. 1 shows that bids in the market treatment are very close to those in the two baselines in the first 50 periods. In fact, the discrepancy between bids in the market and the two baseline treatments increases over time, as shown by the positive and significant term "Period × Market" in regression Table V.1 (in OSM V). Our findings thus demonstrate that investors do not immediately bid at higher values in the market treatment than in the baselines, suggesting that experiencing arousal after winning bids is necessary for any anticipated emotion to impact bidding behavior. An interesting avenue for future research would be to study the interaction between anticipated and experienced emotions in market settings. A first step in that direction is the study by Bossaerts et al. (2023), which uses a continuous double auction to study the impact of anticipatory emotions on traders' performance.

5.3. Social preferences

The role of social preferences has also been investigated as a potential cause for overbidding in auctions. However, it is important to note that evidence for spite has been both demonstrated and theorized in the context of private-value auctions (Cooper and Fang, 2008; Bartling and Netzer, 2016; Kirchkamp and Mill, 2021; Mill and Morgan, 2022). By contrast, in our study, investors were not assigned a private valuation for the asset, thus preventing, for example, a low-valuation investor from envying a high-valuation investor. Furthermore, we did not prompt identity types, as Mill and Morgan (2022) did with political preferences in the United States, thereby limiting the role of spiteful behavior.

5.4. Attention

The critical difference between the market treatment and the two baseline treatments is that a trader's outcome depends on the bids of others. This design feature introduces strategic uncertainty and could explain differences between treatments that are not solely tied to competition. One could argue that the baseline treatments induce a high level of boredom during the experiment, which is not observed in the market treatment, which may sustain a higher level of trader engagement than the baseline treatments, resulting in higher bids. To assess this claim, we consider two alternative measures of engagement. First, we consider the likelihood of not making a decision in a given period. This likelihood was overall higher in the market treatment (6.6%) than in the baselines (2.1%), suggesting that participants were not less attentive and engaged in the baseline treatments (see Fig. V.1 in OSM V). Furthermore, market is the only treatment in which the likelihood of not making a decision increased during the experiment, from around 3.1% in the first 10 periods to up to 8.2% in period 100 (see Fig. V.1 in OSM V). However, the regression results in Table V.2 in OSM V show that the previous treatment differences are not significant (see non-significant coefficients for "Market," "Baseline-feedback", "Market × Period" and "Baseline-feedback × Period" in regression (1)). Overall, these results suggest that attention to the task was not significantly different across treatments, and they continue to hold when considering separately investors who exhibited low and high base rate arousal (see Table V.3 in OSM V).[40] Our findings are thus unlikely to be explained by differences in boredom and fatigue across treatments.

5.5. Rare losses

One might wonder whether the occurrence of rare losses, which is a specific feature of our experimental design inspired by CCH and earlier works on tail events (e.g., Hertwig et al., 2004), could explain the observed treatment differences. Indeed, as shown in Table 2 (see also CCH), rare losses incurred in the previous period led to higher bids. However, this rare loss effect does not differ significantly across treatments, as shown in Table V.4 in OSM V, which replicates Table 2 and adds interaction effects between the treatment dummies and the occurrence of a rare loss in the previous period (see insignificant coefficients for "Market × Large loss dummy in $t-1''$ and "Baseline-feedback × Loss dummy in $t-1''$ and the coefficient test between these two variables). These analyses suggest that the prior occurrence of losses does not explain treatment differences in bidding behavior. Furthermore, the increase in bids in the market compared to the baseline and baseline-feedback treatments continues to be observed when considering only sessions in which rare losses occurred at most once – a frequency lower than the median occurrence rate of two (see "Market × Zero-to-one rare losses dummy," which is never negative and significant in Table V.5 in OSM V).

Finally, one might still wonder whether differences in physiological responses across treatments will be unduly impacted by the occurrence of rare losses. However, as for the case of bids, we show in Table V.6 in OSM V that the interaction effects between the treatment dummies and the occurrence of a rare loss in the previous period are not significant. Overall, our findings suggest that rare losses are not a key driver of treatment differences.

5.6. Heterogeneity in risk attitudes

Although all treatments are designed to encourage investors to bid their true value (see simulation results in OSM II), differences across treatments may arise because deviating from this strategy might be more tempting in the market treatment. Unlike in the baselines, highly risk-averse investors in the market treatment will be unable to accumulate earnings if they bid their value because

[40] Our second measure, decision arousal, also shows that there is no difference between treatments (see Fig. V.1 and Tables V.2 and V.3 in OSM V).

their bid will never be strictly higher than the price. As a result, these investors may bid above their value to increase their chances of winning the auction, thereby remaining engaged in the experiment. This behavior could potentially help explain the larger increase in bids in the market treatment compared to the baselines.

To test this potential explanation, we use the risk elicitation measure from our survey. Following Holt and Laury (2002), we classify investors as highly risk-averse if they chose the safe option eight times or more, which accounts for 12.2% of the participants in our sample.[41] We also consider an alternative measure that accounts for an investor's relative risk aversion within his or her experimental group, which we refer to as "Rank risk". This relative measure of risk aversion is a dummy variable that takes a value of one if a person is the most risk-averse person in his or her group (11.8% of the people in our sample).[42]

Regardless of the measure used and at odds with the proposed explanation, the increase in bids in the market treatment compared to the baselines (see Table 2) was not more pronounced for the subset of highly risk-averse investors, as is shown in Tables V.7 and V.8 in OSM V (see "Market × High-risk aversion dummy" and "Market × Rank risk", which are not significant and are often negative), and continued to be significant when considering all investors who were not highly risk-averse (see "Market" in all regressions in both tables). Furthermore, heightened arousal after buying the asset in the market treatment (see Table 3) was not more pronounced, regardless of the measure, for the subset of highly risk-averse investors, as is shown in Tables V.9 and V.10 in OSM V (see "Market × Win × High-risk aversion dummy" and "Market × Win × Rank risk", which are not significant), and continued to be significant when considering all investors who were not highly risk-averse (see "Market" in all regressions in both tables).

5.7. Loss aversion and prospect theory

Although simulation results based on expected utility and the prospect theory model considered in OSM II show no differences across treatments, the increase in bids in the market compared to the baseline treatment could potentially be explained by loss aversion, assuming a sufficiently high reference point. In the prospect theory model considered in OSM II, the reference point was set at the investor's endowment of 1200¢. However, loss aversion may trigger risk-seeking behavior when considering higher reference points that reflect, for example, the expected gains in a standard laboratory experiment where the study was conducted. To investigate this possibility, we conducted simulations based on the prospect theory model with higher reference points. Indeed, as the reference point increases to 1700¢ and 2200¢, and assuming a reasonable loss aversion value of 1.5 or 2.0 (see, e.g., Kahneman and Tversky, 1979; Gonzalez and Wu, 1999; L'Haridon and Vieider, 2019), we observe higher bids than with a reference point of 1200¢ in both the market and baseline treatments (see Fig. V.2 in OSM V). Interestingly, the increase in bids is more pronounced in the market than in the baseline treatment, as investors remain in the loss domain for longer, thus triggering more risk-seeking behavior. In the baseline condition, investors reach their reference point between periods 50 and 100, thus causing an early decrease in bids. The widening gap in bids across treatments arises because the early increase in bids leads to slightly higher prices in the market, implying a slower accumulation of wealth. However, with an even higher reference point (2700¢), bids increase substantially in the baseline treatment, because investors remain in the loss domain for longer, and ultimately converge to the levels observed in the market treatment.

For intermediate values of the reference point, loss aversion can thus explain the dynamics in bids in both the market and baseline treatment, with an initial surge in bids followed by a decrease in bids toward the end of the experiment. It can also explain the larger increase in bids in the market treatment than in baseline. However, these simulations fall short of explaining the level of bids, which in the market treatment is about 25% higher on average than the asset's expected value from period 50 to period 250. Furthermore, prospect theory is a consequentialist theory that discards the role of emotions (Loewenstein et al., 2011), and as such fails to explain the heightened physiological response of investors when buying assets in the market treatment. It also fails to account for why differences across treatments tend to disappear for investors who exhibit low base rate arousal. In addition, we fail to find a significant relationship between the degree of loss aversion and participants' bid in the market treatment (See Table A13 in Appendix A.4). We, therefore, posit that the specifications of prospect theory should be complemented by an explicit joy of winning function, whose importance would vary depending on the trading institution. In particular, the joy of winning does not seem to be magnified solely by social comparisons (see baseline-feedback) but rather by competition among investors.

6. Conclusion

Our study is the first to provide causal evidence that markets trigger specific emotions. These emotional responses, which are unique to the market institution, are characterized by investors experiencing heightened emotional arousal when competing successfully against other traders. Interestingly, the exacerbated emotional response to winning bids in markets was more pronounced when asset payoffs were high. This suggests that competitive arousal made investors more sensitive to cash earnings. This phenomenon can be viewed as a physiological measure of greed, which is heightened in markets. Overall, our results indicate that the distinctive feature of markets only produces behavioral differences due to the associated emotional arousal. Indeed, bids did not differ between market and non-market institutions for investors who exhibited low base rate emotional arousal. For investors exhibiting high base rate arousal, the market institution may be particularly detrimental because it exacerbates emotions and induces lower gains due to a higher risk of bankruptcy.

[41] These are investors who exhibit a coefficient of relative risk aversion strictly greater than 0.97. Similar results hold if we consider investors who opted for the safe option seven times or more (34.5% of the people in our sample), who are described by Holt and Laury (2002) as very risk-averse.
[42] Similar results hold if we consider the two most risk-averse people in the group (28.4% of the people in our sample).

Interestingly, competitive arousal induces aroused traders to bid at higher levels while not impacting their unaroused counterparts, thus creating heterogeneity in bidding behavior. In a market in which speculation is possible, these heterogenous reactions could further facilitate the development of bubbles since even traders with low base rate arousal will be willing to bid high to resell to traders that do experience higher arousal. This mechanism relates to behavioral models of speculative bubbles in which traders are assumed to hold heterogenous beliefs due to overconfidence in the asset value (Abreu and Brunnermeier, 2003; Scheinkman and Xiong, 2003; Hong et al., 2006). Our study can provide a physiological foundation for the persistence of heterogenous beliefs ingrained in traders' varying arousal responses to market outcomes.

It might be tempting to use our findings to motivate the adoption of venting techniques (e.g., Bushman, 2002; Xiao and Houser, 2005; Bolle et al., 2014; Dickinson and Masclet, 2015; Steenbarger, 2015) and other emotional regulation strategies (Astor et al., 2014; Kandasamy et al., 2016) to mitigate overbidding in markets. However, mitigating emotional arousal could have the unintended consequence of quieting anticipatory emotional responses related to fear and anxiety that can help traders avoid excessive risk (Bechara et al., 1997; Bossaerts et al., 2023).

Given the limitations of the emotional regulation approach (Raio et al., 2013), our paper offers an appealing alternative that involves redesigning existing institutions. Doing so can reduce competitive arousal without necessarily impacting the other emotional responses that are necessary to making successful investment decisions.

Because we wanted to compare our market treatment with non-market baselines, we have focused on a specific one-sided auction format. However, we believe that competitive arousal is an integral part of any market institution, including two-sided markets used in major exchanges, such as call and continuous double auctions. An interesting avenue for future research could involve examining how to mitigate competitive arousal in two-sided markets, for instance, by using algorithmic traders (Bao et al., 2022; Asparouhova et al., 2024; Corgnet et al., 2024b).

Author's contribution

All authors contributed equally.

Declaration of interests

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Nobuyuki Hanaki reports financial support was provided by Japan Society for the Promotion of Science andFrench National Research Agency. Brice Corgnet and Camille Cornand reports financial support was provided by French National Research Agency.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jedc.2026.105382.

Appendix. : Robustness of results

A.1. Hypotheses 1 and 2

Table A1
Bids and quadratic trend fitting.

Treatment	Baseline	Baseline-Feedback	Market	All
	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE	Bid			
Period	0.0163***	0.0296***	0.0544***	0.0163***
	(0.0059)	(0.0109)	(0.0185)	(0.0059)
$Period^2$	−0.0001****	−0.0002****	−0.0002****	−0.0001****
	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)
Market				−0.9884
				(1.2620)
Market × Period				0.0381**
				(0.0192)
Market × $Period^2$				−0.0001
				(0.0001)
Baseline-feedback				−0.4540
				(1.0507)
Baseline-feedback × Period				0.0133
				(0.0122)
Baseline-feedback × $Period^2$				−0.0001
				(0.0001)
Constant	25.2204****	24.7664****	24.2327****	25.2207****
	(0.5119)	(0.9315)	(1.1710)	(0.5086)

(continued on next page)

Table A1 (*continued*)

Treatment	Baseline	Baseline-Feedback	Market	All
	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE	Bid			
Quadratic trend features				
Peak period	67	96	133	—
Peak value	25.76	26.18	27.85	—
Peak overpricing as % of expected value	11.2%	13.0%	20.1%	—
Period such that Bid = Expected value	212	235	284	—
R^2	0.0442	0.0377	0.0146	0.0404
Observations	68,071	47,074	43,293	158,438
Number of investors	241	167	152	560

*$p < 0.1$. "Bid = Expected value" was calculated solving the corresponding equation of degree 2 given the estimated coefficients for Period and Period^2 in each treatment. Market (baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the market (baseline-feedback) treatment.

**** $p < 0.001$,

*** $p < 0.01$,

** $p < 0.05$,

A.2. Hypothesis 3

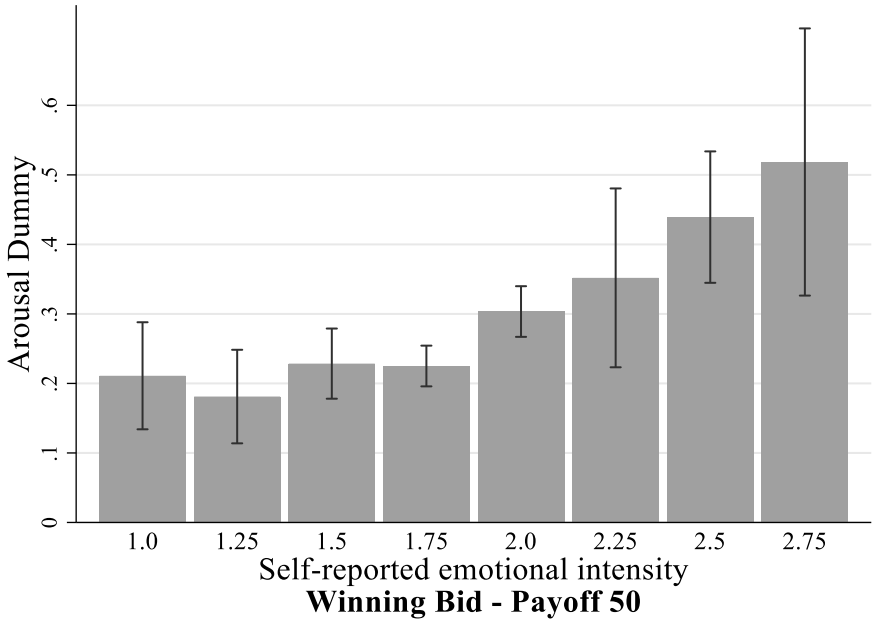


Fig. A.1. Arousal dummy as a function of self-reported emotional intensity for the case of a payoff of 50 and a winning bid. Self-reported emotional intensity was calculated as the average Likert scale answer on the four basic emotions for the case of winning bid and a payoff of 50.

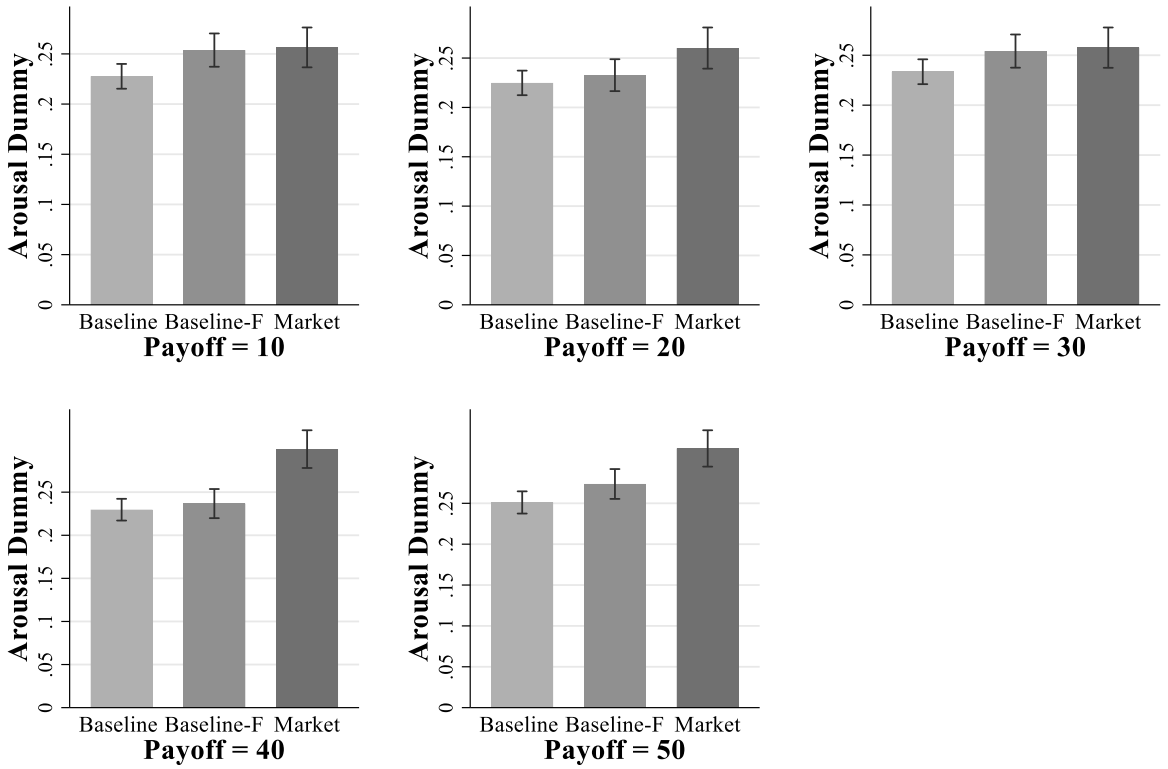


Fig. A.2. Emotional arousal for winning bids across treatments and asset payoffs; Baseline-F stands for baseline-feedback.

Table A2
Arousal and winning bids in the first 40 periods. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level are in (1) and (2). In (3) and (4), autoregressive (AR(1)) errors are used, and no period variable and period fixed effects are included. Negative payoffs periods are excluded from the analysis (99.2% of the data are included); (std) stands for standardized variables.

DEPENDENT VARIABLE	(1) Arousal Dummy	(2)	(3)	(4)
Market × Win	0.0853****	0.0863****	0.0842****	0.0847****
	(0.0216)	(0.0220)	(0.0190)	(0.0265)
Market	−0.0168	−0.0225	−0.0159	−0.0214
	(0.0192)	(0.0237)	(0.0266)	(0.0264)
Baseline-feedback × Win	0.0586**	0.0565**	0.0539***	0.0514***
	(0.0227)	(0.0228)	(0.0176)	(0.0177)
Baseline-feedback	0.0046	0.0000	0.0060	−0.0068
	(0.0272)	(0.0276)	(0.0257)	(0.0256)
Win	0.0312**	0.0309**	0.0321***	0.0321***
	(0.0133)	(0.0133)	(0.0109)	(0.0110)
Bid	0.0012**	0.0013**	0.0009	0.0010**
	(0.0006)	(0.0006)	(0.0005)	(0.0005)
Number of large losses up to $t-2$	0.0201	0.0198	−0.0025	−0.0022
	(0.0231)	(0.0227)	(0.0201)	(0.0200)
Asset payoff	−0.0000	−0.0000	0.0001	−0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Asset payoff in $t-1$	0.0002	0.0003	0.0002	0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Large loss dummy in $t-1$	0.3108	0.3480	0.1880	0.2189
	(0.3036)	(0.3103)	(0.2732)	(0.2748)
Period	−0.0038****	−0.0038****		
	(0.0008)	(0.0008)		
Male dummy (std)		0.0319***		0.0318***
		(0.0099)		(0.0103)
Risk aversion (std)		0.0129		0.0131
		(0.0087)		(0.0099)
Loss aversion (std)		−0.0068		−0.0071
		(0.0102)		(0.0100)

(*continued on next page*)

Table A2 (*continued*)

DEPENDENT VARIABLE	(1) Arousal Dummy	(2)	(3)	(4)
Constant	0.3226****	0.3220****	0.2184****	0.2186****
	(0.0365)	(0.0364)	(0.0224)	(0.0223)
Coefficient tests				
Market × Win =Baseline−feedback × Win	0.2971	0.2518	0.1532	0.1183
Market = Baseline-feedback	0.4908	0.4352	0.4629	0.4362
R^2	0.0176	0.0239	0.0081	0.0142
Observations	13,006	12,854	13,006	12,854
Number of investors	344	340	344	340

*$p < 0.1$. Market (baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the market (baseline-feedback) treatment. Win is a dummy that takes a value of one if a participant bought the asset in a given period. Number of large losses up to $t-2$ equals the number of times a participant faced an asset paying off a large loss up to period $t-2$. Large loss dummy in $t-1$ takes a value of one if a participant faced an asset paying off a large loss in the previous period. Risk aversion {Loss} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}.

**** $p < 0.001$,

*** $p < 0.01$,

** $p < 0.05$,

Table A3

Arousal and winning bids. Panel probit regressions with random effects and period fixed effects along with robust standard errors clustered at the session level are in (1) and (2). In (3) and (4), autoregressive (AR(1)) errors are used, and no period variable and period fixed effects are included. Negative payoffs periods are excluded from the analysis (99.2% of the data are included); (std) stands for standardized variables.

DEPENDENT VARIABLE	(1) Arousal Dummy	(2)	(3)	(4)
Market × Win	0.2038****	0.2018****	0.1898****	0.1884****
	(0.0460)	(0.0466)	(0.0395)	(0.0402)
Market	−0.0600	−0.0647	−0.0611	−0.0655
	(0.0643)	(0.0638)	(0.0636)	(0.0632)
Baseline-feedback × Win	0.0908***	0.0885***	0.0734**	0.0718**
	(0.0340)	(0.0339)	(0.0283)	(0.0284)
Baseline-feedback	−0.0358	−0.0446	−0.0260	−0.0348
	(0.0567)	(0.0582)	(0.0570)	(0.0587)
Win	0.0415**	0.0437**	0.0476***	0.0491***
	(0.0182)	(0.0182)	(0.0154)	(0.0155)
Bid	0.0001	0.0009	0.0013	0.0021*
	(0.0014)	(0.0014)	(0.0013)	(0.0012)
Number of large losses up to $t-2$	0.0031	0.0013	−0.0231	−0.0234
	(0.0206)	(0.0203)	(0.0157)	(0.0155)
Asset payoff	0.0018****	0.0017****	0.0017****	0.0017****
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Asset payoff in $t-1$	−0.0004	−0.0005	−0.0003	−0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Large loss dummy in $t-1$	−0.4728	−0.5365	−0.3754	−0.4326
	(0.3242)	(0.3274)	(0.3124)	(0.3159)
Period	−0.0006****	−0.0006****		
	(0.0002)	(0.0002)		
Male dummy (std)		0.0711***		0.0719***
		(0.0257)		(0.0257)
Risk aversion (std)		0.0182		0.0216
		(0.0219)		(0.0220)
Loss aversion (std)		−0.0014		−0.0016
		(0.0289)		(0.0287)
Constant	−0.7276****	−0.7484****	−0.8285****	−0.8415****
	(0.0583)	(0.0552)	(0.0531)	(0.0498)
Coefficient tests				
Market × Win = Baseline-feedback × Win	0.0174	0.0198	0.0050	0.0059
Market = Baseline-feedback	0.7302	0.7786	0.6159	0.6672
Observations	96,264	95,243	96,264	95,243
Number of investors	344	340	344	340

*$p < 0.1$. Market (baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the market (baseline-feedback) treatment. Win is a dummy that takes a value of one if a participant bought the asset in a given period. Number of large losses up to $t-2$ equals the number of times a participant faced an asset paying off a large loss up to period $t-2$. Large loss dummy in $t-1$ takes a value of one if a participant faced an asset paying off a large loss in the previous period. Risk aversion {Loss} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}.

**** $p < 0.001$,

*** $p < 0.01$,

** $p < 0.05$,

Table A4
Arousal dummy and winning bids; instrumental variable (IV regression) panel regressions with random effects along with robust standard errors in parentheses. Instrument used for Win is Price$^{\perp}$; (std) stands for standardized variables.

DEPENDENT VARIABLE	(1) Arousal dummy	(2)
Market × Win	0.0498****	0.0495****
	(0.0104)	(0.0105)
Market	0.0027	0.0018
	(0.0187)	(0.0186)
Baseline-feedback × Win	0.0093	0.0088
	(0.0075)	(0.0076)
Baseline-feedback	0.0037	−0.0001
	(0.0166)	(0.0169)
Win	0.0272****	0.0276****
	(0.0045)	(0.0046)
Number of large losses up to $t-2$	0.0121**	0.0129***
	(0.0048)	(0.0048)
Asset payoff	−0.0003****	−0.0003****
	(0.0000)	(0.0000)
Asset payoff in $t-1$	0.0001	0.0001
	(0.0001)	(0.0001)
Large loss dummy in $t-1$	0.0976	0.0890
	(0.0940)	(0.0946)
Period	−0.0002****	−0.0002****
	(0.0001)	(0.0001)
Male dummy (std)		0.0239***
		(0.0079)
Risk aversion (std)		0.0060
		(0.0064)
Loss aversion (std)		0.0015
		(0.0086)
Constant	0.2357****	0.2370****
	(0.0128)	(0.0126)
Coefficient tests		
Market × Win =Baseline-feedback × Win	< 0.0001	< 0.0001
R^2	0.0075	0.0101
Observations	97,022	95,995
Number of investors	344	340

*$p < 0.1$. Market (Baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the Market (Baseline-feedback) treatment. Win is a dummy that takes a value of one if a participant bought the asset in a given period. Negative payoff periods are excluded from the analysis (99.2% of the data are included). Number of large losses up to $t-2$ equals the number of times a participant faced an asset paying off a large loss up to period $t-2$. Large loss dummy in $t-1$ takes a value of one if a participant faced an asset paying off a large loss in the previous period. Risk Aversion {Loss aversion} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}.

**** $p < 0.001$,
*** $p < 0.01$,
** $p < 0.05$,

Table A5
Emotion reported by participants at the end of the experiment (Baseline-feedback treatment) for the four basic valenced emotions after winning and non-winning bids. Only participants who effectively placed a winning (non-winning) bid for a given payoff were asked to report their emotions. Mean (median) responses for a Likert scale ranged from 1 = *Not at all* to 5 = *Extremely*. SD stands for standard deviation. In brackets, we also report sign rank test *p*-values for the hypothesis that the reported emotion is moderate (Answer 3 on the 5-point Likert scale).

Payoff 50	Winning Bid	Non-winning bid	Payoff 10	Winning Bid	Non-winning bid
Anger	1.10 (1.00)	2.02 (2.00)	Anger	1.67 (1.00)	1.28 (1.00)
	SD = 0.43	SD = 1.12		SD = 0.92	SD = 0.64
	[p < 0.001]	[p < 0.001]		[p < 0.001]	[p < 0.001]
Fear	1.22 (1.00)	1.18 (1.00)	Fear	1.41 (1.00)	1.18 (1.00)
	SD = 0.58	SD = 0.52		SD = 0.71	SD = 0.61
	[p < 0.001]	[p < 0.001]		[p < 0.001]	[p < 0.001]
Joy	3.81 (4.00)	1.18 (1.00)	Joy	1.53 (1.00)	2.06 (1.00)
	SD = 1.10	SD = 0.62		SD = 0.80	SD = 1.18
	[p < 0.001]	[p < 0.001]		[p < 0.001]	[p < 0.001]
Sadness	1.03 (1.00)	2.39 (2.00)	Sadness	1.76 (2.00)	1.34 (2.00)
	SD = 0.18	SD = 1.12		SD = 0.88	SD = 0.75
	[p < 0.001]	[p < 0.001]		[p < 0.001]	[p < 0.001]

All *p*-value inequalities continue to hold using the Holm-Bonferroni procedure, given that we report the results of 16 tests in the table.

Table A6
Arousal and winning bids with low vs. high payoff interaction effects. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in (1) and (2). In (3) and (4), autoregressive errors (AR(1)) are used, and no period variable and period fixed effects are included; (std) stands for standardized variables.

DEPENDENT VARIABLE	(1) Arousal dummy	(2)	(3)	(4)
Market × Win × High payoff	0.0341**	0.0341**	0.0296***	0.0298***
	(0.0170)	(0.0172)	(0.0099)	(0.0099)
Market × Win	0.0332***	0.0334***	0.0387****	0.0390****
	(0.0105)	(0.0106)	(0.0090)	(0.0091)
Market	−0.0015	−0.0029	−0.0045	−0.0060
	(0.0196)	(0.0182)	(0.0192)	(0.0191)
Baseline-feedback × Win	0.0082	0.0078	0.0084	0.0081
	(0.0083)	(0.0084)	(0.0070)	(0.0070)
Baseline-feedback	0.0033	−0.0004	0.0033	−0.0003
	(0.0194)	(0.0191)	(0.0183)	(0.0183)
Win	0.0188****	0.0188****	0.0187****	0.0189****
	(0.0044)	(0.0044)	(0.0043)	(0.0044)
Bid	0.0014****	0.0015****	0.0017****	0.0017****
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Number of large losses up to $t-2$	0.0118*	0.0125*	−0.0005	−0.0002
	(0.0068)	(0.0068)	(0.0022)	(0.0022)
Asset payoff	0.0004***	0.0004***	0.0004****	0.0004****
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Asset payoff in $t-1$	0.0000	−0.0000	−0.0000	−0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Large loss dummy in $t-1$	0.0101	−0.0042	−0.0252	−0.0370
	(0.1160)	(0.1170)	(0.1080)	(0.1086)
Period	−0.0004***	−0.0004***		
	(0.0002)	(0.0002)		
Male dummy (std)		0.0245***		0.0245***
		(0.0077)		(0.0077)
Risk aversion (std)		0.0082		0.0090
		(0.0061)		(0.0075)
Loss aversion (std)		0.0020		0.0017
		(0.0093)		(0.0075)
Constant	0.3299****	0.3312****	0.1629****	0.1632****
	(0.0361)	(0.0363)	(0.0130)	(0.0130)
R^2	0.0097	0.0126	0.0027	0.0055
Observations	76,162	75,358	76,162	75,358
Number of investors	344	340	344	340

Market (Baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the Market (Baseline-feedback) treatment. Win is a dummy that takes a value of one if a participant bought the asset in a given period. High payoff is a dummy taking a value of one when payoffs were above the median payoff of 30. The median payoff of 30 is not included in the regression to enable directly comparing low (10 or 20) and high (40 or 50) payoffs. Negative payoff periods are excluded from the analysis (99.2% of the data are included). Number of large losses up to $t-2$ equals the number of times a participant faced an asset paying off a large loss up to period $t-2$. Large loss dummy in $t-1$ takes a value of one if a participant faced an asset paying off a large loss in the previous period. Risk aversion {Loss aversion} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}.

**** $p < 0.001$,
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Table A7
Arousal and winning bids with payoff interaction effects. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in (1) and (2). In (3) and (4), autoregressive errors (AR(1)) are used, and no period variable and period fixed effects are included; (std) stands for standardize variables.

DEPENDENT VARIABLE	(1) Arousal dummy	(2)	(3)	(4)
Market × Win × Payoff	0.0011**	0.0011**	0.0011****	0.0010****
	(0.0005)	(0.0005)	(0.0003)	(0.0003)
Market × Win	0.0130	0.0132	0.0144	0.0143
	(0.0130)	(0.0133)	(0.0115)	(0.0116)
Market	0.0003	−0.0006	0.0003	−0.0008
	(0.0192)	(0.0178)	(0.0188)	(0.0187)
Baseline-feedback × Win	0.0108	0.0105	0.0095	0.0091
	(0.0085)	(0.0086)	(0.0063)	(0.0063)
Baseline-feedback	0.0030	−0.0005	0.0041	0.0007
	(0.0194)	(0.0190)	(0.0179)	(0.0179)
Win	0.0210****	0.0211****	0.0215****	0.0218****
	(0.0044)	(0.0045)	(0.0039)	(0.0039)
Bid	0.0013****	0.0013****	0.0014****	0.0014****
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of large losses up to $t-2$	0.0107	0.0114*	−0.0025	−0.0022
	(0.0066)	(0.0066)	(0.0016)	(0.0017)
Asset payoff	0.0003***	0.0003***	0.0004****	0.0004****
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Asset payoff in $t-1$	0.0001	0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Large loss dummy in $t-1$	0.0699	0.0583	0.0298	0.0198
	(0.1008)	(0.1017)	(0.0953)	(0.0958)
Period	−0.0003**	−0.0003**		
	(0.0001)	(0.0001)		
Male dummy (std)		0.0248***		0.0249****
		(0.0077)		(0.0076)
Risk aversion (std)		0.0078		0.0085
		(0.0062)		(0.0073)
Loss aversion (std)		0.0017		0.0014
		(0.0090)		(0.0074)
Constant	0.3141****	0.3139****	0.1667****	0.1671****
	(0.0256)	(0.0256)	(0.0122)	(0.0122)
R^2	0.0084	0.0113	0.0027	0.0056
Observations	96,264	95,243	96,264	95,243
Number of investors	344	340	344	340

Market (Baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the Market (Baseline-feedback) treatment. Win is a dummy that takes a value of one if a participant bought the asset in a given period. Negative payoff periods are excluded from the analysis (99.2% of the data are included). Number of large losses up to $t-2$ equals the number of times a participant faced an asset paying off a large loss up to period $t-2$. Large loss dummy in $t-1$ takes a value of one if a participant faced an asset paying off a large loss in the previous period. Risk aversion {Loss aversion} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}.

**** $p < 0.001$,
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Table A8
Arousal and winning bids with money gain interaction effects. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in (1) and (2). In (3) and (4), autoregressive errors (AR(1)) are used, and no period variable and period fixed effects are included; (std) stands for standardized variables.

DEPENDENT VARIABLE	(1) Arousal dummy	(2)	(3)	(4)
Market × Win × Money gain	0.0239*	0.0226*	0.0238**	0.0225**
	(0.0125)	(0.0128)	(0.0093)	(0.0093)
Market × Win	0.0294**	0.0300**	0.0299***	0.0304***
	(0.0118)	(0.0121)	(0.0092)	(0.0092)
Market	0.0002	−0.0007	0.0001	−0.0009
	(0.0192)	(0.0178)	(0.0188)	(0.0187)

(*continued on next page*)

Table A8 (*continued*)

DEPENDENT VARIABLE	(1) Arousal dummy	(2)	(3)	(4)
Baseline-feedback × Win	0.0108	0.0105	0.0095	0.0092
	(0.0085)	(0.0086)	(0.0063)	(0.0063)
Baseline-feedback	0.0030	−0.0005	0.0041	0.0007
	(0.0194)	(0.0190)	(0.0179)	(0.0179)
Win	0.0209****	0.0210****	0.0215****	0.0217****
	(0.0044)	(0.0045)	(0.0039)	(0.0039)
Bid	0.0013****	0.0013****	0.0014****	0.0014****
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of large losses up to $t-2$	0.0108	0.0115*	−0.0025	−0.0022
	(0.0066)	(0.0066)	(0.0016)	(0.0017)
Asset payoff	0.0004****	0.0004***	0.0005****	0.0005****
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Asset payoff in $t-1$	0.0001	0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Large loss dummy in $t-1$	0.0729	0.0614	0.0326	0.0226
	(0.1011)	(0.1020)	(0.0953)	(0.0958)
Period	−0.0003**	−0.0003**		
	(0.0001)	(0.0001)		
Male dummy (std)		0.0248***		0.0249****
		(0.0077)		(0.0076)
Risk aversion (std)		0.0078		0.0085
		(0.0062)		(0.0073)
Loss aversion (std)		0.0017		0.0013
		(0.0090)		(0.0074)
Constant	0.3118****	0.3116****	0.1648****	0.1652****
	(0.0254)	(0.0253)	(0.0122)	(0.0122)
R^2	0.0084	0.0113	0.0026	0.0055
Observations	96,264	95,243	96,264	95,243
Number of investors	344	340	344	340

Market (Baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the Market (Baseline-feedback) treatment. Win is a dummy that takes a value of one if a participant bought the asset in a given period. Money gain is a dummy taking a value of one when investors obtain a monetary gain in a given period. Negative payoff periods are excluded from the analysis (99.2% of the data are included). Number of large losses up to $t-2$ equals the number of times a participant faced an asset paying off a large loss up to period $t-2$. Large loss dummy in $t-1$ takes a value of one if a participant faced an asset paying off a large loss in the previous period. Risk aversion {Loss aversion} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}.

**** $p < 0.001$,
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Table A9

Bids and treatment effects for investors with low base rate arousal. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in (1) and (2). In (3) and (4), autoregressive (AR(1)) errors are used, and no period variable and period fixed effects are included; (std) stands for standardized variables.

Low base rate arousal investors DEPENDENT VARIABLE	(1) Bid	(2)	(3)	(4)
Market	0.7022	0.9786	0.7547	1.0039
	(1.5562)	(1.5591)	(1.3683)	(1.3265)
Baseline-feedback	−0.8700	−0.6674	−0.4781	−0.2734
	(1.4497)	(1.4624)	(1.4631)	(1.4437)
Physio dummy	27.4513****	26.9178****		
	(1.2196)	(1.1898)		
Number of large losses up to $t-2$	0.7819*	0.8437*	−1.1019****	−1.1003****
	(0.4709)	(0.4675)	(0.0970)	(0.0972)
Asset payoff in $t-1$	0.0199****	0.0203****	0.0205****	0.0209****
	(0.0047)	(0.0047)	(0.0026)	(0.0026)
Large loss dummy in $t-1$	20.5932****	21.0393****	20.0471****	20.4427****
	(4.9850)	(4.9710)	(2.7298)	(2.7496)
Period	−0.0434****	−0.0442****		
	(0.0070)	(0.0070)		
Male dummy (std)		−0.5870		−0.7172
		(0.6778)		(0.5913)
Risk aversion (std)		−1.4495***		−1.4872***
		(0.5182)		(0.5267)
Loss aversion (std)		0.3705		0.2638
		(0.4118)		(0.5701)

(*continued on next page*)

Table A9 (*continued*)

Low base rate arousal investors DEPENDENT VARIABLE	(1) Bid	(2)	(3)	(4)
Constant			26.1283****	25.6132****
			(0.8286)	(0.8197)
Coefficient tests				
Market = Baseline-feedback	0.3809	0.3320	0.4503	0.4176
Market = Baseline-combined	0.5140	0.4130	0.4820	0.3780
Lee bounds				
Market = Baseline	(−0.371**, 3.3288***)			
Market = Baseline-feedback	(0.962****, 2.406****)			
Market = Baseline-combined	(0.060, 3.041****)			
R^2	0.0440	0.0687	0.0098	0.0325
Observations	33,548	33,253	33,548	33,253
Number of investors	119	118	119	118

Market (Baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the Market (Baseline-feedback) treatment. Physio dummy is a dummy that takes a value of one if a participant was assigned to a session in which physiological recording were used. Baseline-combined is a dummy variable taking a value of one if a person was assigned to one of the two baseline treatments. This test reports the results for the regression in which the only treatment dummy is Baseline-combined. Number of large losses up to $t-2$ equals the number of times a participant faced an asset paying off a large loss up to period $t-2$. Large loss dummy in $t-1$ takes a value of one if a participant faced an asset paying off a large loss in the previous period. Risk aversion {Loss aversion} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}. Estimates of lower and upper bounds following the procedure in Lee (2009) accounting for selection issues due to the missing bidding data of bankrupt participants (4.4% of the data). We used 1000 replications for the bootstrapped standard errors.

**** $p < 0.001$,
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Table A10

Bids and treatment effects for investors with high base rate arousal. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level appear in (1) and (2). In (3) and (4), autoregressive (AR(1)) errors are used, and no period variable and period fixed effects are included; (std) stands for standardized variables.

High base rate arousal investors DEPENDENT VARIABLE	(1) Bid	(2)	(3)	(4)
Market	4.1266*	3.9826**	3.9745***	3.8011***
	(2.1478)	(1.8450)	(1.4876)	(1.4597)
Baseline-feedback	3.1379**	2.0405	3.3029***	2.2776*
	(1.2857)	(1.3666)	(1.2691)	(1.2750)
Physio dummy	31.0256****	26.6468****		
	(1.6045)	(1.3048)		
Number of large losses up to $t-2$	0.1478	0.1449	−1.2898****	−1.2783****
	(0.4391)	(0.4405)	(0.0864)	(0.0867)
Asset payoff in $t-1$	0.0107**	0.0104**	0.0141****	0.0137****
	(0.0052)	(0.0052)	(0.0019)	(0.0019)
Large loss dummy in $t-1$	11.7568**	11.4180**	14.1714****	13.7152****
	(5.1801)	(5.2320)	(1.9742)	(1.9836)
Period	−0.0617****	−0.0454****		
	(0.0084)	(0.0072)		
Male dummy (std)		−0.9458*		−0.9376*
		(0.5541)		(0.5655)
Risk aversion (std)		−1.6962**		−1.4860***
		(0.6841)		(0.5605)
Loss aversion (std)		−0.4356		−0.3980
		(0.5173)		(0.5359)
Constant			23.4128****	23.8290****
			(0.7826)	(0.7816)
Coefficient tests				
Market = Baseline-feedback	0.6537	0.3131	0.6782	0.3418
Market = Baseline-combined	0.1580	0.0620	0.0580	0.0340
Lee Bounds				
Market = Baseline	(3.156****, 6.910****)			
Market = Baseline-feedback	(0.333*, 2.287****)			
Market = Baseline-combined	(2.062****, 5.423****)			
R^2	0.0663	0.0975	0.0831	0.1065
Observations	41,591	41,166	41,591	41,166
Number of investors	152	150	152	150

Market (Baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the Market (Baseline-feedback) treatment. Physio dummy is a dummy that takes a value of one if a participant was assigned to a session in which physiological recording was used. Baseline-combined is a dummy variable taking a value of one if a person was assigned to one of the two baseline treatments. This test reports the results for the regression in

which the only treatment dummy is Baseline-combined. Number of large losses up to $t-2$ equals the number of times a participant faced an asset paying off a large loss up to period $t-2$. Large loss dummy in $t-1$ takes a value of one if a participant faced an asset paying off a large loss in the previous period. Risk aversion {Loss aversion} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}. Estimates of lower and upper bounds follow the procedure in Lee (2009) to account for selection issues due to the missing bidding data of bankrupt participants (6.9% of the data). We used 1000 replications for the bootstrapped standard errors.

**** $p < 0.001$,
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

A.3. Earnings and bankruptcy rates

Table A11

Final earnings (in ¢) as a function of base rate arousal, treatment dummies, and individual controls. Ordinary least squares regressions with robust standard errors clustered at the individual level. Regressions (1) and (2) consider all physio sessions, and regressions (3) and (4) consider sessions in which at least two negative payoffs were drawn (68.9% of the data); (std) stands for standardized variables.

DEPENDENT VARIABLE	(1) Earnings (¢)	(2)	(3)	(4)
Base rate arousal	39.3103	45.0626	98.4853	97.3822
	(51.4263)	(44.9425)	(62.4423)	(65.6939)
Market	−191.6862	−184.1349	381.0387	356.3781
	(243.5186)	(280.5862)	(321.6154)	(325.0031)
Market × Base rate arousal	−165.5089*	−169.0087*	−280.2235**	−272.2101**
	(88.7706)	(86.9218)	(124.2218)	(124.3335)
Baseline-feedback	372.9449	322.2874	475.3355	402.1810
	(278.3205)	(359.0928)	(472.2676)	(477.5135)
Baseline-feedback × Base rate arousal	−79.8332	−50.4491	−114.8014	−76.0486
	(97.3599)	(72.5050)	(107.5761)	(96.4366)
Number of negative payoffs	−409.3336****	−402.6040****	−190.2332	−192.1182
in a session	(50.5046)	(99.9947)	(189.0979)	(189.5547)
Male dummy (std)		7.6228		12.4411
		(71.7152)		(92.3680)
Risk aversion (std)		−23.1100		−27.2819
		(59.1271)		(81.6115)
Loss aversion (std)		−36.4742		−47.5107
		(56.5094)		(77.8082)
Constant	3903.6759****	3870.2122****	2988.0134****	3000.0339****
	(171.9186)	(241.3569)	(540.4861)	(552.1176)
Coefficient tests				
Market × Base rate arousal =Baseline-feedback × Base rate arousal	0.4338	0.2624	0.2251	0.1452
R^2	0.2000	0.2011	0.0458	0.0527
Observations	338	334	232	230

$^{***}p < 0.01$, Market (Baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the Market (Baseline-Feedback) treatment. Risk aversion {Loss aversion} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}.

**** $p < 0.001$,
** $p < 0.05$,
* $p < 0.1$.

Table A12

Bankruptcy as a function of base rate arousal, treatment dummies, and individual controls. Probit regressions with robust standard errors clustered at the individual level. Regressions (1) and (2) consider all physio sessions, and regressions (3) and (4) consider sessions in which at least two negative payoffs were drawn (68.9% of the data); (std) stands for standardized variables.

DEPENDENT VARIABLE	(1) Bankruptcy Dummy	(2)	(3)	(4)
Base rate arousal	−0.1434*	−0.1561*	−0.1667*	−0.1888**
	(0.0813)	(0.0838)	(0.0854)	(0.0881)
Market	−0.9991**	−1.0139**	−1.8015****	−1.8260****
	(0.4692)	(0.4701)	(0.4301)	(0.4102)
Market × Base rate arousal	0.3712**	0.3819**	0.6037****	0.6156****
	(0.1678)	(0.1678)	(0.1545)	(0.1482)
Baseline-feedback	−0.6185	−0.5561	−0.5783	−0.5446
	(0.4093)	(0.4098)	(0.4193)	(0.4274)
Baseline-feedback	0.2455*	0.1976	0.2420*	0.2109
× Base rate arousal	(0.1457)	(0.1488)	(0.1470)	(0.1525)
N umber of negative payoffs	0.1906***	0.1979***	−0.1670	−0.1521
in a session	(0.0616)	(0.0631)	(0.1138)	(0.1154)
Male dummy (std)		0.0640		0.1219

(*continued on next page*)

Table A12 (*continued*)

DEPENDENT VARIABLE	(1) Bankruptcy Dummy	(2)	(3)	(4)
		(0.0968)		(0.1074)
Risk aversion (std)		−0.0490		−0.0302
		(0.1038)		(0.1155)
Loss aversion (std)		0.0486		0.0631
		(0.0910)		(0.1045)
Constant	−1.2912****	−1.2858****	−0.0628	−0.0609
	(0.2332)	(0.2419)	(0.3820)	(0.3982)
Coefficient tests				
Market × Base rate arousal =Baseline-feedback × Base rate arousal	0.5025	0.3213	0.0387	0.0193
Pseudo-R^2	0.0528	0.0557	0.0712	0.0751
Observations	338	334	232	230

Bankruptcy dummy takes a value of one if a participant went bankrupt during the experiment. Market (Baseline-feedback) is a dummy that takes a value of one if a participant was assigned to the Market (Baseline-feedback) treatment. Risk aversion {Loss aversion} is measured as the switching point in Holt and Laury (2002) (OSM I, Block 1) {Brink and Rankin, 2013, Block 4}.

**** $p < 0.001$,
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

A.4. Loss aversion

Table A13

Bids and loss aversion for the market treatment. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level are in (1). In (2), autoregressive (AR(1)) errors are used, and no period variable and period fixed effects are included; (std) stands for standardized variables.

DEPENDENT VARIABLE	(1) Bid	(2)
Physio dummy	1.6299	1.6713
	(1.6908)	(1.2017)
Number of large losses up to $t-2$	0.6778	−0.3681****
	(0.7360)	(0.1053)
Asset payoff in $t-1$	0.0227****	0.0252****
	(0.0057)	(0.0026)
Large loss dummy in $t-1$	24.5903****	25.7455****
	(5.7334)	(2.6816)
Period	−0.0354****	
	(0.0081)	
Male dummy (std)	−0.1943	−0.1915
	(0.6168)	(0.6009)
Risk aversion (std)	−0.4354	−0.4593
	(0.6285)	(0.5962)
Loss aversion (std)	−0.6143	−0.5976
	(0.6846)	(0.6397)
Constant	23.6712****	24.8664****
	(1.6264)	(0.8839)
R^2	0.0341	0.0149
Observations	42,691	42,691
Number of investors	151	151

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
**** $p < 0.001$.

A.5. Additional analyses on mispricing

We further investigated potential differences in the temporal patterns of mispricing by analyzing bubble duration, a classical measure in the experimental asset market literature (Smith et al., 1988; Porter and Smith, 1995; Palan, 2009). We define bubble duration as the longest sequence of consecutive periods during which prices both increase and remain above the asset's fundamental value.[43] Because our experimental design consists of 300 trading periods—twenty times longer than the original design of Smith et al. (1988), which has become the standard in the literature—we first aggregated observations into blocks of 20 periods. For each market, we computed the average bid within each block and then defined bubble duration as:

[43] This measure is called positive duration (see Palan, 2009).

$$\text{Duration} = \max_{g}\left(m : \bar{b}_g - f_g < \bar{b}_{g+1} - f_{g+1} < \ldots < \bar{b}_{g+m} - f_{g+m}\right) \; s.t. \; \bar{b}_{g+1} > f_{g+1}$$

Where $\bar{b}_g$ is the average bid in a market in time block g, and the 300 trading periods are divided into 15 consecutive blocks of 20 periods each. We also note that our results are robust to using time blocks of 10, 30 or 50 instead. Thus, the duration measure captures the longest run of consecutive blocks in which the degree of overpricing increases while prices remain above fundamental value.

Using this measure, we find that average bubble duration is 2.41 in the market-treatment, compared with 2.14 in baseline-feedback (a 12.3% increase) and 1.86 in baseline (a 29.2% increase). Both differences are statistically significant (Rank Sum tests, $p < 0.001$). These findings corroborate our analyses in the main text and suggest that the treatments primarily affect the magnitude and persistence of mispricing rather than the existence of bubbles themselves.

References

Abreu, D., Brunnermeier, M.K., 2003. Bubbles and crashes. Econom. J. Econom. Soc. 71, 173–204. https://doi.org/10.1111/1468-0262.00393.

Adam, M.T.P., Krämer, J., Müller, M.B., 2015. Auction fever! how time pressure and social competition affect bidders' arousal and bids in retail auctions. J. Retail. 91, 468–485. https://doi.org/10.1016/j.jretai.2015.01.003.

Akiyama, E., Hanaki, N., Ishikawa, R., 2017. It is not just confusion! strategic uncertainty in an experimental asset market. Econ. J. 127, F563–F580. https://doi.org/10.1111/ecoj.12338.

Aliber, R.Z., Kindleberger, C.P., McCauley, R.N., 2023. Manias, Panics, and Crashes: A History of Financial Crises, 8th ed. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-031-16008-0.

Andrade, E.B., Odean, T., Lin, S., 2015. Bubbling with excitement: an experiment. Rev. Financ. 20, 447–466. https://doi.org/10.1093/rof/rfv016.

Apesteguia, J., Oechssler, J., Weidenholzer, S., 2020. Copy trading. Manag. Sci. 66, 5608–5622. https://doi.org/10.1287/mnsc.2019.3508.

Asparouhova, E., Bossaerts, P., Cai, P., Rotaru, X.K., Yadav, N., Yang, W., 2024. Humans in charge of trading robots: the first experiment. Rev. Financ. 28, 1215–1244. https://doi.org/10.1093/rof/rfae007.

Astor, P., Adam, M., Jerčić, P., Schaaff, K., Weinhardt, C., 2014. Integrating biosignals into information systems: a NeuroIS tool for improving emotion regulation. J. Manag. Inf. Syst. JMIS 30 (3), 247–277. https://doi.org/10.2753/MIS0742-1222300309.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21 (2), 129–151. https://doi.org/10.1257/jep.21.2.129.

Bao, T., Nekrasova, E., Neugebauer, T., Riyanto, Y.E., 2022. Algorithmic trading in experimental markets with human traders: a literature survey. In: Füllbrun, S., Haruvy, E. (Eds.), Handbook of Experimental Finance. Edward Elgar, pp. 302–322.

Barrett, L.F., Adolphs, R., Marsella, S., Martinez, A.M., Pollak, S.D., 2019. Emotional expressions reconsidered: challenges to inferring emotion from human facial movements. Psychol. Sci. Public Interest 20 (1), 1–68.

Bartling, B., Netzer, N., 2016. An externality-robust auction: theory and experimental evidence. Games Econ. Behav. 97, 186–204. https://doi.org/10.1016/j.geb.2016.04.004.

Bault, N., Joffily, M., Rustichini, A., Coricelli, G., 2011. Medial prefrontal cortex and striatum mediate the influence of social comparison on the decision process. Proc. Natl. Acad. Sci. U. S. A. 108, 16044–16049. https://doi.org/10.1073/pnas.1100892108.

Bechara, A., Damasio, A.R., 2005. The somatic marker hypothesis: a neural theory of economic decision. Games Econ. Behav. 52, 336–372. https://doi.org/10.1016/j.geb.2004.06.010.

Bechara, A., Damasio, H., Tranel, D., Damasio, A.R., 1997. Deciding advantageously before knowing the advantageous strategy. Science 275, 1293–1295. https://doi.org/10.1126/science.275.5304.1293 *(1979)*.

Becker, G.M., DeGroot, M.H., Marschak, J., 1964. Measuring utility by a single-response sequential method. Behav. Sci. 9, 226–232. https://doi.org/10.1002/bs.3830090304.

Bleichrodt, H., Wakker, P.P., 2015. Regret theory: a bold alternative to the alternatives. Econ. J. 125, 493–532. https://doi.org/10.1111/ecoj.12200.

Bolle, F., Tan, J.H.W., Zizzo, D.J., 2014. Vendettas. Am. Econ. J. Microecon. 6 (2), 93–130.

Bosch-Rosa, C., Meissner, T., Bosch-Domènech, A., 2018. Cognitive bubbles. Exp. Econ. 21, 132–153.

Bossaerts, P., Fattinger, F., Rotaru, K., Xu, K., 2023. Emotional engagement and trading performance. Manag. Sci. 70, 3381–3397. https://doi.org/10.1287/mnsc.2023.4883.

Boucsein, W., 2012. Electrodermal Activity. Springer Science & Business Media.

Breaban, A., Deck, C., Johnson, E., 2022. Emotional differences between isomorphic auctions. J. Behav. Finance 23, 427–437. https://doi.org/10.1080/15427560.2022.2081972.

Breaban, A., Noussair, C.N., 2017. Emotional state and market behavior. Rev. Financ. 22, 279–309. https://doi.org/10.1093/rof/rfx022.

Brink, A.G., Rankin, F.W., 2013. The effects of risk preference and loss aversion on individual behavior under bonus, penalty, and combined contract frames. Behav. Res. Account. 25 (2), 145–170.

Bursztyn, L., Ederer, F., Ferman, B., Yuchtman, N., 2014. Understanding mechanisms underlying peer effects: evidence from a field experiment on financial decisions. Econom. J. Econom. Soc. 82, 1273–1301. https://doi.org/10.3982/ECTA11991.

Bushman, B.J., 2002. Does venting anger feed or extinguish the flame? Catharsis, rumination, distraction, anger, and aggressive responding. Person. Soc. Psychol. Bull. 28 (6), 724–731.

Christopoulos, G.I., Uy, M.A., Yap, W.J., 2019. The body and the brain: measuring skin conductance responses to understand the emotional experience. Organ Res. Methods 22, 394–420. https://doi.org/10.1177/1094428116681073.

Cooper, D.J., Fang, H., 2008. Understanding overbidding in second price auctions: an experimental study. Econ. J. 118, 1572–1595. https://doi.org/10.1111/j.1468-0297.2008.02181.x.

Corazzini, L., Greiner, B., 2007. Herding, social preferences and (Non-)conformity. Econ. Lett. 97, 74–80. https://doi.org/10.1016/j.econlet.2007.02.024.

Corgnet, B., C. Cornand, and N. Hanaki. 2020. "Tail events, emotions and risk taking." Working paper. 10.2139/ssrn.3606079.

Corgnet, B., Cornand, C., Hanaki, N., 2024a. Negative tail events, emotions and risk taking. Econ. J. 134, 538–578. https://doi.org/10.1093/ej/uead080.

Corgnet, B., DeSantis, M., Porter, D., 2018. What makes a good trader? On the role of intuition and reflection on trader performance. J. Finance 73, 1113–1137. https://doi.org/10.1111/jofi.12619.

Corgnet, B., M. DeSantis, and C. Siemroth. 2024b. "Algorithmic trading, price efficiency and welfare: an experimental approach." Working paper. 10.2139/ssrn.4419304.

Corgnet, B., Hernán-González, R., 2019. Revisiting the trade-off between risk and incentives: the shocking effect of random shocks? Manag. Sci. 65, 1096–1114. https://doi.org/10.1287/mnsc.2017.2914.

Coventry, K.R., Constable, B., 1999. Physiological arousal and sensation-seeking in female fruit machine gamblers. Addiction 94, 425–430. https://doi.org/10.1046/j.1360-0443.1999.94342512.x.

Coventry, K.R., Hudson, J., 2001. Gender differences, physiological arousal and the role of winning in fruit machine gamblers. Addiction 96, 871–879. https://doi.org/10.1046/j.1360-0443.2001.9668718.x.

Cox, J.C., Smith, V.L., Walker, J.M., 1988. Theory and individual behavior of first-price auctions. J. Risk Uncertain. 1, 61–99. https://doi.org/10.1007/BF00055565.
Critchley, H.D., Elliott, R., Mathias, C.J., Dolan, R.J., 2000. Neural activity relating to generation and representation of galvanic skin conductance responses: a functional magnetic resonance imaging study. J. Neurosci.: The Official Journal of the Society for Neuroscience 20 (8), 3033–3040.
Damasio, A.R., 1996. The somatic marker hypothesis and the possible functions of the prefrontal cortex. Philos. Trans. R. Soc. Lond. 351, 1413–1420. https://doi.org/10.1098/rstb.1996.0125. *Series B, Biological Sciences*.
Damasio, A.R., Carvalho, G.B., 2013. The nature of feelings: evolutionary and neurobiological origins. Nature Rev. Neurosci. 14, 143–152. https://doi.org/10.1038/nrn3403.
Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. J. Finance 53, 1839–1885. https://doi.org/10.1111/0022-1082.00077.
Delgado, M.R., Schotter, A., Ozbay, E.Y., Phelps, E.A., 2008. Understanding overbidding: using the neural circuitry of reward to design economic auctions. Science 321, 1849–1852. https://doi.org/10.1126/science.1158860 *(1979)*.
Deutsch, M., 1949. A theory of co-operation and competition. Human Relat. 2, 129–152. https://doi.org/10.1177/001872674900200204.
Dickinson, D.L., Masclet, D., 2015. Emotion venting and punishment in public good experiments. J. Public Econ. 122, 55–67.
Dijk, O., Holmen, M., Kirchler, M., 2014. Rank matters – The impact of social competition on portfolio choice. Eur. Econ. Rev. 66, 97–110. https://doi.org/10.1016/j.euroecorev.2013.11.010.
Ekman, P., 1992. Are there basic emotions? Psychol. Rev. 99, 550–553. https://doi.org/10.1037/0033-295X.99.3.550.
Engelbrecht-Wiggans, R., Katok, E., 2006. Regret in auctions: theory and evidence. Econ. Theory 33, 81–101. https://doi.org/10.1007/s00199-006-0180-9.
Engelbrecht-Wiggans, R., Katok, E., 2008. Regret and feedback information in first-price sealed-bid auctions. Manag. Sci. 54, 808–819. https://doi.org/10.1287/mnsc.1070.0806.
Eyster, E., Rabin, M., Vayanos, D., 2019. Financial markets where traders neglect the informational content of prices. J. Finance 74, 371–399. https://doi.org/10.1111/jofi.12729.
Fafchamps, M., Kebede, B., Zizzo, D.J, 2015. Keep up with the winners: experimental evidence on risk taking, asset integration, and peer effects. Eur. Econ. Rev. 79, 59–79. https://doi.org/10.1016/j.euroecorev.2015.07.001.
Fama, E.F., 2014. Two pillars of asset pricing. Am. Econ. Rev. 104, 1467–1485. https://doi.org/10.1257/aer.104.6.1467.
Fiske, A.P., 1991. Structures of Social Life – The Four Elementary Forms of Human Relations: Communal Sharing, Authority Ranking, Equality Matching, Market Pricing. The Free Press, New York.
Frydman, C. 2015. "What drives peer effects in financial decision-making? Neural and behavioral evidence." Working paper. 10.2139/ssrn.2561083.
Georganas, S., Levin, D., McGee, P., 2017. Optimistic irrationality and overbidding in private value auctions. Exp. Econ. 20, 772–792. https://doi.org/10.1007/s10683-017-9510-y.
Goeree, J.K., Holt, C.A., Palfrey, T.R., 2002. Quantal response equilibrium and overbidding in private-value auctions. J. Econ. Theory 104, 247–272. https://doi.org/10.1006/jeth.2001.2914.
Golub, G.H., Van Loan, C.F., 2013. Matrix Computations, 4th ed. Johns Hopkins University Press.
Gonzalez, R., Wu, G., 1999. On the shape of the probability weighting function. Cogn. Psychol. 38, 129–166. https://doi.org/10.1006/cogp.1998.0710.
Gortner, P.J., van der Weele, J.J., 2019. Peer effects and risk sharing in experimental asset markets. Eur. Econ. Rev. 116, 129–147. https://doi.org/10.1016/j.euroecorev.2019.04.001.
Greenwood, R., Shleifer, A., You, Y., 2019. Bubbles for Fama. J. Financ. Econ. 131, 20–43. https://doi.org/10.1016/j.jfineco.2018.09.002.
Hertwig, R., Barron, G., Weber, E., Erev, I., 2004. Decisions from experience and the effect of rare events in risky choice. Psychol. Sci. 15, 534–539. https://doi.org/10.1111/j.0956-7976.2004.00715.x.
Hirshleifer, D., 2020. Presidential address: social transmission bias in economics and finance. J. Finance 75, 1779–1831. https://doi.org/10.1111/jofi.12906.
Holt, C.A., Laury, S.K., 2002. Risk aversion and incentive effects. Am. Econ. Rev. 92 (5), 1644–1655.
Hong, H., Kubik, J.D., Stein, J.C., 2004. Social interaction and stock-market participation. J. Finance 59, 137–163. https://doi.org/10.1111/j.1540-6261.2004.00629.x.
Hong, H., Kubik, J.D., Stein, J.C., 2005. Thy neighbor's portfolio: word-of-mouth effects in the holdings and trades of money managers. J. Finance 60, 2801–2824. https://doi.org/10.1111/j.1540-6261.2005.00817.x.
Hong, H., Scheinkman, J., Xiong, W., 2006. Asset float and speculative bubbles. J. Finance 61, 1073–1117. https://doi.org/10.1111/j.1540-6261.2006.00867.x.
Hong, H., Stein, J.C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. J. Finance 54, 2143–2184. https://doi.org/10.1111/0022-1082.00184.
Joffily, M., 2018. Electrodermal Activity (EDA) Toolbox. GitHub Repository. https://github.com/mateusjoffily/EDA.
Joffily, M., Coricelli, G., 2013. Emotional valence and the free-energy principle. PLoS Comput. Biol. 9 (6), e1003094. https://doi.org/10.1371/journal.pcbi.1003094.
Kagel, J.H., Harstad, R.M., Levin, D., 1987. Information impact and allocation rules in auctions with affiliated private values: a laboratory study. Econom. J. Econom. Soc. 55, 1275–1304. https://doi.org/10.1515/9781400830138.177.
Kagel, J.H., Levin, D., 2016. Auctions a survey of experimental research. In: Kagel, J.H., Levin, D. (Eds.), The Handbook of Experimental Economics. Princeton University Press, Princeton, NJ, pp. 563–637. https://doi.org/10.1515/9781400883172-010.
Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econom. J. Econom. Soc. 47, 363–391. https://doi.org/10.2307/1914185.
Kandasamy, N., Garfinkel, S.N., Page, L., Hardy, B., Critchley, H.D., Gurnell, M., Coates, J.M., 2016. Interoceptive ability predicts survival on a London trading floor. Sci. Rep. 6, 32986. https://doi.org/10.1038/srep32986.
Kaustia, M., Knüpfer, S., 2012. Peer performance and stock market entry. J. Financ. Econ. 104, 321–338. https://doi.org/10.1016/j.jfineco.2011.01.010.
Kelly, M., Gráda, C.Ó, 2000. Market contagion: evidence from the panics of 1854 and 1857. Am. Econ. Rev. 90, 1110–1124. https://doi.org/10.1257/aer.90.5.1110.
Keltner, D., Cordaro, D.T., 2017. Understanding multimodal emotional expressions: recent advances in basic emotion theory. In: Fernández-Dols, J.-M., Russell, J.A. (Eds.), The Science of Facial Expression. Oxford University Press, pp. 57–75.
Keynes, J.M, 1936. The General Theory of Employment, Interest, and Money. Palgrave Macmillan, London.
Kirchkamp, O., Mill, W., 2021. Spite vs. risk: explaining overbidding in the second-price all-pay auction. Games Econ. Behav. 130, 616–635. https://doi.org/10.1016/j.geb.2021.10.003.
Kirchler, M., Lindner, F., Weitzel, U., 2018. Rankings and risk-taking in the finance industry. J. Finance 73, 2271–2302. https://doi.org/10.1111/jofi.12701.
Kirchler, M., Lindner, F., Weitzel, U., 2020. Delegated investment decisions and rankings. J. Bank Financ. 120, 105952. https://doi.org/10.1016/j.jbankfin.2020.105952.
Ku, G., Malhotra, D., Keith Murnighan, J., 2005. Towards a competitive arousal model of decision-making: a study of auction fever in live and internet auctions. Organ. Behav. Hum. Decis. Process. 96, 89–103. https://doi.org/10.1016/j.obhdp.2004.10.001.
Kuchler, T., Stroebel, J., 2021. Social finance. Annu. Rev. Financ. Econ. 13, 37–55. https://doi.org/10.1146/annurev-financial-101320-062446.
Kuziemko, I., Buell, R.W., Reich, T., Norton, M.I., 2014. 'Last-place aversion': evidence and redistributive implications. Q. J. Econ. 129, 105–149. https://doi.org/10.1093/qje/qjt035.
Lahno, A.M., Serra-Garcia, M., 2015. Peer effects in risk taking: envy or conformity? J. Risk Uncertain. 50, 73–95. https://doi.org/10.1007/s11166-015-9209-4.
Lee David, S., 2009. Training, wages, and sample selection: estimating sharp bounds on treatment effects. Rev. Econ. Stud. 76, 1071–1102.

Lei, V., Noussair, C.N., Plott, C.R., 2001. Nonspeculative bubbles in experimental asset markets: lack of common knowledge of rationality vs. actual irrationality. Econom. J. Econom. Soc. 69, 831–859. https://doi.org/10.1111/1468-0262.00222.
L'Haridon, O., Vieider, F., 2019. All over the map: a worldwide comparison of risk preferences. Quant. Econom. 10, 185–215. https://doi.org/10.3982/QE898.
Lindner, F., Kirchler, M., Rosenkranz, S., Weitzel, U., 2021. Social motives and risk-taking in investment decisions. J. Econ. Dyn. Control 127, 104116. https://doi.org/10.1016/j.jedc.2021.104116.
Lo, A.W., 2013. Fear, greed, and financial crises: a cognitive neurosciences perspective. In: Fouque, J.P., Langsam, J.A. (Eds.), Handbook on Systemic Risk. Cambridge University Press, Cambridge, pp. 622–662. https://doi.org/10.1017/CBO9781139151184.032.
Lo, A.W., 2017. Adaptive markets: financial evolution at the speed of thought. Adaptive Markets. Princeton University Press, Princeton, NJ. https://doi.org/10.1515/9781400887767.
Lo, A.W., Repin, D.V., 2002. The psychophysiology of real-time financial risk processing. J. Cogn. Neurosci. 14, 323–339. https://doi.org/10.1162/089892902317361877.
Lo, A.W., Repin, D.V., Steenbarger, B.N., 2005. Fear and greed in financial markets: a clinical study of day-traders. Am. Econ. Rev. 95, 352–359. https://doi.org/10.1257/000282805774670095.
Loewenstein, G.F., Weber, E.U., Hsee, C.K., Welch, N., 2001. Risk as feelings. Psychol. Bull. 127, 267–286. https://doi.org/10.1037//0033-2909.127.2.267.
Loomes, G., Sugden, R., 1982. Regret theory: an alternative theory of rational choice under uncertainty. Econ. J. 92, 805–824. https://doi.org/10.2307/2232669.
Malhotra, D., 2010. The desire to win: the effects of competitive arousal on motivation and behavior. Organ. Behav. Hum. Decis. Process. 111 (2), 139–346. https://doi.org/10.1016/j.obhdp.2009.11.005.
Malmendier, U., Lee, Y.H, 2011. The Bidder's curse. Am. Econ. Rev. 101, 749–787. https://doi.org/10.1257/aer.101.2.749.
Martinez, A.M., 2019. The promises and perils of automated facial action coding in studying children's emotions. Dev. Psychol. 55 (9), 1965.
Mengel, F., Peeters, R., 2022. Do markets encourage risk-seeking behaviour? Eur. J. Finance 28, 1474–1480. https://doi.org/10.1080/1351847x.2020.1828963.
Meyer, A., Attali, Y., Bar-Hillel, M., Frederick, S., Kahneman, D., 2024. Cognitive reflection is a distinct and measurable trait. Proc. Natl. Acad. Sci. U. S. A. 121, e2409191121. https://doi.org/10.1073/pnas.2409191121.
Mill, W., Morgan, J., 2022. Competition between friends and foes. Eur. Econ. Rev. 147, 104171. https://doi.org/10.1016/j.euroecorev.2022.104171.
Noussair, C.N., Tucker, S., 2013. A collection of surveys on market experiments. In: Noussair, C.N., Tucker, S. (Eds.), A Collection of Surveys on Market Experiments. John Wiley & Sons, Hoboken, NJ, pp. 1–4. https://doi.org/10.1002/9781118790700.ch1.
Noussair, C., Robin, S., Ruffieux, B., 2004. Revealing consumers' willingness-to-pay: a comparison of the BDM mechanism and the Vickrey auction. J. Econ. Psychol. 25 (6), 725–741.
Oechssler, J., Roider, A., Schmitz, P.W., 2009. Cognitive abilities and behavioral biases. J. Econ. Behav. Organ. 72, 147–152.
Palan, S., 2013. A review of bubbles and crashes in experimental asset markets. In: Noussair, C.N., Tucker, S. (Eds.), A collection of Surveys on Market Experiments. John Wiley & Sons, Hoboken, NJ, pp. 197–217. https://doi.org/10.1002/9781118790700.ch10.
Plott, C.R., Sunder, S., 1982. Efficiency of experimental security markets with insider information: an application of rational-expectations models. J. Political Econ. 90 (4), 663–698.
Plott, C.R., Sunder, S., 1988. Rational expectations and the aggregation of diverse information in laboratory security markets. Econom. J. Econom. Soc. 56, 1085–1118.
Plutchik, R., 2001. The nature of emotions: human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. Am. Sci. 89, 344–350. https://www.jstor.org/stable/27857503.
Pokorny, K., 2008. Pay – But do not pay too much: an experimental study on the impact of incentives. J. Econ. Behav. Organ. 66, 251–264. https://doi.org/10.1016/j.jebo.2006.03.007.
Polanyi, K., 1944. The Great Transformation. Farrar & Rinehart, New York.
Pollak, S.D., Camras, L.A., Cole, P.M., 2019. Progress in understanding the emergence of human emotion. Dev. Psychol. 55 (9), 1801.
Porter, D., Smith, V.L., 1995. Futures contracting and dividend uncertainty in experimental asset markets. J. Bus. 68 (4), 509–541.
Potters, J., Suetens, S., 2013. Oligopoly experiments in the current millennium. In: Noussair, C.N., Tucker, S. (Eds.), A Collection of Surveys on Market Experiments. John Wiley & Sons, Hoboken, NJ, pp. 51–74. https://doi.org/10.1002/9781118790700.ch4.
Rabin, M., 2002. Inference by believers in the law of small numbers. Q. J. Econ. 117, 775–816. https://doi.org/10.1162/003355302760193896.
Raio, C.M., Orederu, T.A., Palazzolo, L., Shurick, A.A., Phelps, E.A., 2013. Cognitive emotion regulation fails the stress test. Proc. Natl. Acad. Sci. U. S. A. 110, 15139–15144. https://doi.org/10.1073/pnas.1305706110.
Rottenberg, J., Ray, R., Gross, J., 2007. Emotion elicitation using films. In: Coan, J.A., Allen, J.B. (Eds.), Handbook of Emotion Elicitation and Assessment. Oxford University Press, Oxford, pp. 9–28.
Sahlins, M., 2013. Stone Age Economics. Routledge, London.
Scheinkman, J.A., Xiong, W., 2003. Overconfidence and speculative bubbles. J. Political Econ. 111, 1183–1220. https://doi.org/10.1086/378531.
Schoenberg, E.J., Haruvy, E., 2012. Relative performance information in asset markets: an experimental approach. J. Econ. Psychol. 33, 1143–1155. https://doi.org/10.1016/j.joep.2012.08.008.
Schwerter, F., 2024. Social reference points and risk taking. Manag. Sci. 70, 616–632. https://doi.org/10.1287/mnsc.2023.4698.
Seuntjens, T.G., Zeelenberg, M., Breugelmans, S.M., Ven, N., 2014. Defining greed. Br. J. Psychol. 106, 505–525. https://doi.org/10.1111/bjop.12100.
Seuntjens, T.G., Zeelenberg, M., van de Ven, N., Breugelmans, S.M., 2015. Dispositional greed. J. Pers. Soc. Psychol. 108, 917–933. https://doi.org/10.1037/pspp0000031.
Shefrin, H. (Ed.), 2007. Beyond Greed and Fear. Oxford University Press, New York. https://doi.org/10.1093/oso/9780195304213.001.0001.
Shields, G.S., Sazma, M.A., Yonelinas, A.P., 2016. The effects of acute stress on core executive functions: a meta-analysis and comparison with cortisol. Neurosci. Biobehav. Rev. 68, 651–668. https://doi.org/10.1016/j.neubiorev.2016.06.038.
Shiller, R.J., 1981a. Do stock prices move too much to Be justified by subsequent changes in dividends? Am. Econ. Rev. 71, 421–436.
Shiller, R.J., 1981b. The use of volatility measures in assessing market efficiency. J. Finance 36, 291–304. https://doi.org/10.1111/j.1540-6261.1981.tb00441.x.
Shiller, R.J., 1992. Market Volatility. MIT Press, Cambridge, MA.
Shiller, R.J., 2015. Irrational Exuberance, 3rd ed. Princeton University Press, Princeton, NJ.
Shiller, R.J., Fischer, S., Friedman, B.M., 1984. Stock prices and social dynamics. Brookings Pap. Econ. Act. 1984, 457–510. https://doi.org/10.2307/2534436.
Shive, S., 2009. An epidemic model of investor behavior. J. Financ. Quant. Anal. 45, 169–198. https://doi.org/10.1017/s0022109009990470.
Shogren, J.F., Margolis, M., Koo, C., List, J.A., 2001. A random nth-price auction. J. Econ. Behav. Organ. 46, 409–421. https://doi.org/10.1016/s0167-2681(01)00165-2.
Simon, D., and R. Heimer. 2015. "Facebook finance: how social interaction propagates active investing." Working Paper 15-22, Federal Reserve Bank of Cleveland. 10.26509/frbc-wp-201522.
Slovic, P., Finucane, M.L., Peters, E., MacGregor, D.G., 2007. The affect heuristic. Eur. J. Oper. Res. 177, 1333–1352. https://doi.org/10.1016/j.ejor.2005.04.006.
Smith, V., Suchanek, G.L., Williams, A., 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. Econom. J. Econom. Soc. 56, 1119–1151. https://doi.org/10.2307/1911361.
Sornette, D., 2009. Why Stock Markets Crash. Princeton University Press, Princeton, NJ. https://doi.org/10.1515/9781400829552.
Steenbarger, B.N., 2015. Trading Psychology 2.0: From Best Practices To Best Processes. John Wiley & Sons.
Tan, C.H.Y., 2020. Overbidding and matching rules in second-price auctions: an experimental study. J. Behav. Exp. Econ. 84, 101507. https://doi.org/10.1016/j.socec.2019.101507.
Teubner, T., Adam, M., Riordan, R., 2015. The impact of computerized agents on immediate emotions, overall arousal and bidding behavior in electronic auctions. J. Assoc. Inf. Syst. 16 (10). https://doi.org/10.17705/1jais.00412.

Toplak, M.E., West, R.F., Stanovich, K.E., 2011. The cognitive reflection test as a predictor of performance on heuristics-and-biases tasks. Mem. Cognit. 39 (7), 1275–1289. https://doi.org/10.3758/s13421-011-0104-1.

Trautmann, S.T., Vieider, F.M., 2012. Social influences on risk attitudes: applications in economics. In: Roeser, S., Hillerbrand, R., Sandin, P., Peterson, M. (Eds.), Handbook of Risk Theory. Springer Nature, Cham, pp. 575–600. https://doi.org/10.1007/978-94-007-1433-5_22.

Tucker, S., and Y. Xu. 2024a. "Motivations to speculate are the driving forces in experimental asset market bubbles." Working Papers in Economics 24/02, University of Waikato. https://econpapers.repec.org/paper/waieconwp/24_2f02.htm.

Tucker, S., and Y. Xu. 2024b "Nonspeculative bubbles revisited." Working paper. 10.2139/ssrn.4690877.

van den Bos, W., Li, J., Lau, T., Maskin, E., Cohen, J.D., Read Montague, P., McClure, S.M., 2008. The value of victory: social origins of the winner's curse in common value auctions. Judgm. Decis. Mak. 3, 483–492. https://doi.org/10.1017/s1930297500000759.

Wells, F.L., 1924. Review of *social psychology* by floyd allport. Science 59, 440–441. https://doi.org/10.1126/science.59.1533.440.c *(1979)*.

Wulfert, E., Roland, B.D., Hartley, J., Wang, N., Franco, C., 2005. Heart rate arousal and excitement in gambling: winners versus losers. Psychol. Addict. Behav. 19, 311–316. https://doi.org/10.1037/0893-164X.19.3.311.

Xiao, E., Houser, D., 2005. Emotion expression in human punishment behavior. Proc. Natl. Acad. Sci. U. S. A. 102 (20), 7398–7401.