Emotional Markets:

Competitive Arousal, Overbidding and Bubbles

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 markets exacerbate the emotional arousal associated with winning bids, especially when buying the asset leads to substantial earnings. The market treatment exhibits overbidding and bubble dynamics in comparison to the baselines that use a BDM mechanism. Treatment differences disappear for investors who exhibit no base rate emotional arousal. Our study shows that emotions are critical for understanding market outcomes and suggests designing new trading institutions to mitigate competitive arousal and subsequent overbidding in markets.

Keywords: Competitive arousal, trading institutions, feedback, emotions and risk.

JEL codes: C91, C92, G41, D91.

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

1. Introduction

1.1. Emotions in markets

Markets are the cornerstone of modern economies, being an essential tool for the allocation of resources. 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, Suchanek, and Williams 1988; Sornette 2009; Aliber, Kindleberger, and McCauley 2023; Greenwood, Shleifer, and You 2019). Although economists and finance scholars continue to debate the extent of these anomalies (Fama 2014), few would oppose that market prices can, at times, fail to reflect the available information. However, if market prices do not perfectly reflect fundamental information, what factors are they responding to?

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 an excessive weight to small samples (Rabin 2002) and to any information confirming one's prior beliefs (Daniel, Hirshleifer, and Subrahmanyam 1998). Other papers have also emphasized people's inability to extract information from market signals (Hong and Stein 1999; Corgnet, Desantis, and Porter 2018; Eyster, Rabin, and Vayanos 2019).

Although previous research has emphasized cognitive limitations as the main driver of mispricing, a few exceptions in the literature have considered the role of emotions. For example, Andrade, Odean, and Lin (2015) have shown that inducing certain emotions, like excitement, can increase mispricing in experimental markets. In a similar setup, Breaban and Noussair (2017) have assessed traders' emotional state using face-reading software and found that price levels were lower (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) has used physiological recordings to assess traders' arousal over the course of a market experiment. They have shown 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, Repin, and Steenbarger 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, Kindleberger, and McCauley 2023). This emotion rhetoric is also found in behavioral finance writings, which 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 is still in its infancy, we ask a foundational question: are emotions relevant to financial markets? 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, Fischer and Friedman 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 sharply differs from Andrade, Odean, and Lin (2015), which is the only study we are aware of that causally manipulated emotions in markets. Because these authors induced moods with video clips, as is often done in psychology (Rottenberg, Ray and Gross 2007), their focus was on generic emotions such as excitement, sadness and fear. Instead, we manipulated key institutional features of markets –– their social and competitive dimensions –– and assessed how these dimensions impacted 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 more readily reshaped. It follows that if certain emotions induce excessive mispricing, it would be most effective to design a new trading institution that tames these 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-subject experimental design with three treatments: Baseline, Baseline-Feedback and Market. Inspired from Corgnet, Cornand, and Hanaki (2024) (CCH henceforth), the Baseline features an individual investment task, in which investors bid, through a standard incentive compatible BDM mechanism (Becker, DeGroot and Marschak 1964), 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 (1,000 ¢) otherwise. 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 treatment that can be directly compared to the Market treatment as both give investors the same information about others' bids. The Market treatment thus only differs from Baseline-Feedback 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 (see Shogren et al. 2001) to determine the price of the asset. 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 commonly observed in the literature (Corazzini and Greiner 2007; Kirchler, Lindner, and Weitzel 2018; Lahno and Serra-Garcia 2015; Kuziemko et al. 2014; Dijk, Holmen, and Kirchler 2014; Fafchamps, Kebede, and Zizzo 2015; Lindner et al. 2021; Gortner and van der Weele 2019).

In Hypothesis 2, we predict differences between Market and the 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 treatments. In line with the *competitive arousal hypothesis* (Ku, Malhotra, and Murnighan 2005; Malhotra 2010; Adam, Krämer, and Müller 2015), we posit that competition will exacerbate emotional arousal associated with buying the asset and foster overbidding. Because in our experiment, competitive cues are, by design, more pronounced in the Market treatment than in the two baseline treatments, the *competitive arousal hypothesis* suggests bids will be higher in Market than in Baseline and Baseline-Feedback.

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 Market after a winning bid than in the two baseline treatments. Furthermore, we test whether the heightened emotional arousal can account for the higher levels of bids in the Market compared to the two baselines. In particular, Hypothesis 3ii posits that investors who exhibit a high level of base rate emotional arousal will bid higher in Market than in the baseline 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 as overbidding is more pronounced in Market than in the baseline treatments. In line with Hypothesis 3i, we find that emotional arousal, as measured using electrodermal activity (as in CCH) is substantially higher in 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 Market is more pronounced when the asset's payoff was high. This shows that trading in a market 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

Overbidding in auctions

Our study of the causal impact of markets on emotional arousal contributes to several strands of the literature. In the auction literature, our approach sheds new light on the overbidding anomaly (see Cooper and Fang 2008; Kagel and Levin 2016 for a review). In line with previous research using first price (e.g., Cox, Smith, and Walker 1988; Goeree, Holt, and Palfrey 2002) and second price auctions (Kagel, Harstad, and Levin 1987; Cooper and Fang 2008; Tan 2020), we report overbidding in a random n^{th}-price auction. Overbidding is consistently observed over 300 consecutive periods, thereby downplaying explanations of the phenomenon based on participants' learning and lack of understanding (Kagel, Harstad, and Levin 1987; Georganas, Levin, and McGee 2017). Our findings show that overbidding is likely due to competitive arousal, which is inherent to auctions. Exacerbated emotions in auctions could also, if associated with higher stress levels, impair cognitive functions (Shields, Sazma, and Yonelinas 2016) and mediate the effect of inattention that has been identified by Malmendier and Lee (2011) as a main driver of overbidding. Unlike competition, social feedback alone does not explain overbidding. These findings reveal new insights on the study of 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 Baseline-Feedback and Market. 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 critical role of competition over social feedback.

Emotions in markets

The finance literature on emotions is scant and has ignored 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 critical in explaining overbidding in markets. Importantly, traders who display reduced base rate emotional arousal do not exhibit substantial overbidding in Market. 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 that considered in previous works as it specifically relates to the "joy of winning", rather than the disappointment of losing (Delgado et al. 2008).

Furthermore, our approach posits that experienced arousal 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.

Financial bubbles

Our results also provide insights to another prevalent mispricing phenomenon: financial bubbles. Interestingly, we show that, even in the absence of retrading and speculative motives, bubbles and crashes patterns can be observed in markets. Unlike the dominant speculative hypothesis, our results show that it is the competitive nature of the market itself along with the competitive arousal exhibited by human traders that trigger bubbles and crashes.[2] Our findings thus show that exacerbated emotional arousal inherent to market competition can generate mispricing.

[1] One exception is the work of Breaban, Deck, and Johnson (2022) comparing first price and Dutch auctions. However, they do not consider non-auction institutions thus not analyzing the distinct effect of markets.

[2] Although dominant, the speculative hypothesis had been challenged by Lei, Noussair, and Plott (2001) who showed that bubbles could be observed even in the absence of retrading of shares using an experimental setup à la Smith, Suchanek, and Williams (1988). However, the follow-up studies of Tucker and Xu (2024a; 2024b) show that carefully removing speculative motives indeed eliminates bubbles.

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, Smith, and Walker 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 Market is more pronounced when asset payoffs are high. To our knowledge, the only other direct tests of the *competitive arousal hypothesis* in the literature are due to Adam, Krämer, and Müller (2015) and Teubner, Adam, and Riordan (2015) who manipulated 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, measured by heart rates and electrodermal activity, was higher when competing with other human bidders. However, unlike our study, the manipulations of Adam, Krämer, and Müller (2015) and Teubner, Adam, and Riordan (2015) did not directly impact competition but the social dimension of competition as the authors rightly acknowledged.

2. Design

We designed an incentivized experiment that allows us to observe participants' behavioral and physiological reaction to the realization of financial gains and losses in an investment task across trading institutions. We designed three treatments (Baseline, Baseline-Feedback and Market treatments) to disentangle the effect 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 (Section 2.4). In Part 2, participants played a repeated investment task under the three treatments in a between-subject design (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 an asset using the BDM method. At the beginning of each of the 300 periods, participants had to bid for a financial asset that delivered a small positive reward (either 10¢, 20¢, 30¢, 40¢ or 50¢) in 99.33% of the cases and a very large loss (1,000¢) otherwise.

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] The expected value of the asset each period was 23.2¢. 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. If the bid of a participant was greater than or equal to the price, they 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, the earnings for the current period as well as cumulated earnings, which were equal to the initial endowment, composed of Part 1 fixed wage (1,200¢), plus the gains and losses from buying the asset in previous periods.

To make the potential monetary loss associated with investing in an 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 1,000¢ for liquidity reasons, which had to be repaid at the end of the experiment (as in Plott and Sunder 1982; 1988).[4] If the current wealth of participants (including the loan) was no longer sufficient to repay the loan, they would go bankrupt.[5] In that case, participants were not able to purchase the asset anymore 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 on Part 1 and were only rewarded a 5-euro show-up fee.[6]

Because participants can lose all their endowment when they face very large losses, they might believe the experimenter is 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 6 different colors, each of which was associated with a potential return from the asset (blue token = 10¢, red token = 20¢, orange token = 30¢, green token = 40¢, purple token = 50¢, yellow token = -1,000¢). There were 60 tokens of each color, except

[3] It is standard to use a large number of trials in research assessing the impact of electrodermal activity on behavior in stochastic environments (see Bechara et al. 1997).
[4] This loan ensured that participants would have enough cash to bid for the asset even after a very large loss.
[5] Participants would typically go bankrupt when suffering two very large losses.
[6] There is limited liability in our experiment because bankrupt participants did not repay the loan in full. On average, they repaid 73.8% of the loan.

for two yellow tokens. 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.[7] By observing this picture during the experiment, participants could form an estimate of the frequency of occurrence of each token. The distribution of tokens was thus not fully known by participants so as to allow for learning during the experiment.

For the first 15 sessions we conducted (Baseline physio of CCH), one participant, the picker, was randomly selected 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 the tokens with replacement. 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 completion of the task, and 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.[8] The picker was paid a fixed amount of 15 euros, but incurred a 5-euro penalty if the task was not completed within one hour to ensure timely completion of the experiment.[9] During the task, one of the experimenters closely monitored the picker to ensure they followed the procedure. For all the other sessions, instead, we explained that 15 participants, called pickers, had been randomly selected in 15 previous experimental sessions. We precisely explained their role to participants. At the beginning of each of these other sessions, a participant was randomly selected to choose a number between 1 and 15 in order to select the sequence of draws from one of the 15 previous experimental sessions. 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 described above, we implemented a Baseline-Feedback treatment and a Market treatment. The aim of the Baseline-Feedback treatment was to capture the potential effect of social information. In the Baseline-Feedback treatment, 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 period. The only feature that differed between the

[7] 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.

[8] 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 Appendix I.2.

[9] 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.

Baseline and Baseline-Feedback treatments was the additional feedback screen displayed to participants.

In the Market treatment, the same feedback screen (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. In the Market treatment, 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 to determine the price. Those with a bid strictly higher than the price bought the asset.[10] This is similar to a random n^{th}-price auction.[11,12] In our design, prices were similar in Market (Mean = 25.24¢, SD = 12.76¢), Baseline (Mean = 25.80¢, SD = 14.24¢) and Baseline-Feedback (Mean = 25.54¢, SD = 14.28¢). 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), similarly to the BDM mechanism, truth-telling is the dominant strategy in a private value n^{th}-price auction.[13] Comparing the Baseline-Feedback treatment to the Market treatment allows us to capture the impact of competition. 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 Market and Baseline for a broader range of model specifications. In particular, we show no treatment differences in bidding behavior for the class of models studied in CCH that account for the presence of a fixed reference point in income and updating biases (see Online Appendix II).

An English translation of the instructions for the investment task for each of the three treatments is reported in Internal Appendix A.1.

2.3. Measurement of emotions

[10] This implies that nobody would buy the asset if all bids were the same in a given period. However, this never happened in any of the 8,100 cases.
[11] The reason for not using the k^{th}-price auction for the Market treatment (with the number of assets being sold to be (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.
[12] Although the Market treatment was made as comparable 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 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.
[13] Given the absence of communication and the high number of bidders, tacit collusion is very unlikely to be observed in our setup (see Potters and Suetens 2013, for a discussion). 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.

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 1999) 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 have been 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 each participant's second phalanx (palmar surface) of the index and middle fingers of the non-dominant hand using a Velcro strap and isotonic gel. Another experimenter checked the quality of the recordings before the experiment could start. Setting up the physiological equipment took about 20 minutes on average.

In our setup, we recorded electrodermal responses to two types of stimuli:[14] *i*) a decision is made (referred to as decision arousal)[15] 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 sufficient time elapsed between stimuli, we inserted a four-second waiting screen after a decision was made and after the receipt of the end-of-period feedback. A timer on the screen indicated the time participants had to enter a price using a cursor. If participants did not enter a price on the screen and validate their decision on time, the number indicated by the cursor was selected. To prompt participants to make a decision 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.[16]

[14] After a stimulus is observed, the electrodermal activity needs time to rise and this is referred to as latency. Latency is on average about 4 seconds. In the following seconds, the signal rises until it reaches a peak. In the absence of further stimulation, the signal recovers its baseline (pre-stimulus) level.
[15] This relates to what Bechara et al. (1997) refer to as anticipatory arousal.
[16] As explained in CCH, 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 very 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 wanted to avoid that the

In the Baseline-Feedback physio sessions, to get a sense of the valence of the emotions involved, we included a post-experimental survey in which we asked participants about the emotion (anger, fear, joy, and sadness) they felt when they faced a financial asset that induced a 1000 ¢ loss (see Internal Appendix A.2), a financial asset that delivered a 10 ¢ reward or a 50¢ reward (see Internal Appendix A.3).

2.4. Survey

In Part 1, we collected extensive individual information regarding risk, loss and ambiguity attitudes as well as 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 8 blocks of tests that we performed is reported in Online Appendix I.1.[17]

2.5. Protocol

Between November 2018 and October 2023, we invited a total of 560 participants from a participant pool of more than 2,500 students at a major university, where 44% of the participants were males and their average age was 21.8 years old. All the tasks were computerized. We conducted a total of 62 sessions (see Table 1).

Between November 2018 and June 2019, sessions were all conducted in the laboratory. For the Baseline physio sessions, the two parts of the experiment took place on two different days. To limit attrition, participants were only paid the show-up fee (5 euros) 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 euros and a small variable (either positive or negative) amount of pay depending on their decisions in some of the tests, after completion of the repeated investment task. Part 1 lasted for one hour and Part 2 for 3.5 hours. Average earnings were 39 euros approximately. For Baseline, Baseline-Feedback and Market treatments, Part 1 was shortened, lasted for half an hour and was performed on the same day, during the same session as Part 2. Overall, these sessions lasted for

elicitation of emotional valence interfered with the behavior in the investment task and with our physiological recordings. Finally, eliciting emotional valence throughout the investment task would have lengthened an already long experiment.

[17] In sessions implementing Baseline, Baseline-Feedback and Market treatments, we conducted the tests of Blocks 1 to 8. In half of Baseline physio sessions, we conducted 12 blocks (see CCH). In Baseline-Feedback physio sessions, Market physio sessions and half of Baseline physio sessions, for Part 1 to be implementable online within a reasonable duration of 20 minutes, we only conducted the following tests: risk aversion in the gain domain (Block 2), estimation of tokens (Block 5), loss aversion (Block 8), availability heuristic 1 & 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).

3.5 hours on average. Earnings were similar to Baseline physio sessions except that participants did not receive a second show-up fee for their presence on a second day.

Table 1. Treatment sessions

Treatment	Dates	Number of sessions	Number of participants	Composition of groups
Baseline	Between May and June 2019	6	70	9 groups of 6 4 groups of 4[18]
Baseline physio	Between November 2018 and February 2019 and in April 2022	30	171	2 groups of 7 17 groups of 6 11 groups of 5
Baseline-Feedback	Between May and June 2019	5	72	12 groups of 6
Baseline-Feedback physio	Between September and October 2023	8	95	15 groups of 6, 1 group of 5[19]
Market	Between May and June 2019	4	71	11 groups of 6 1 group of 5
Market physio	Between May and December 2022	9	81	6 groups of 6 9 groups of 5

Between April 2022 and October 2023, we ran new waves of Baseline, Baseline-Feedback and Market physio experiments which we pre-registered using 'AsPredicted' (#144573).[20] Part 1 was conducted online and made even shorter, that is about 20 minutes. 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 2.3 above and presented in Internal Appendices A.2 and A.3) and a comprehension quiz for the BDM procedure (see Online Appendix I.4). Part 2 lasted for 3 hours. Earnings were similar to those of non-physio sessions.[21]

3. Hypotheses

[18] The number of participants in each group was irrelevant in the two baseline treatments because only the information about one's own bids were shown on the screen.
[19] One session (n = 12) crashed in period 269. That is why we collected one more session than intended (n = 95, instead of 80).
[20] Available at: https://aspredicted.org/6S7_8QR. Physiological experiments were not possible during Covid times, which explains the time gap between experiments.

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

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.[22]

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.[23] Part of this literature focuses on rank incentives, which are non-monetary incentives related to one's relative position. For example, Kirchler, Lindner, and Weitzel (2018) show that rank incentives increase risk-taking among underperforming professionals, but not among students, when they invest for themselves.[24] Corazzini and Greiner (2007) do not find any effect of others' information in sequential risky decisions in line with Kirchler, Lindner, and Weitzel (2018) results with students. Lindner et al. (2021) extend the analysis of Kirchler, Lindner, and Weitzel (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 for 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, Holmen, and Kirchler (2014) and Fafchamps, Kebede, and Zizzo (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. 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.[25] 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

[22] In the pre-registration document, Hypothesis 1 encompasses Hypotheses 1 and 2, as described in this section. Hypothesis 3 corresponds to Hypotheses 2 and 3 in this section.
[23] See Trautmann and Vieider (2012) for an overview of these effects in decisions under risk.
[24] Kirchler, Lindner, and Weitzel (2020) show that the same result is obtained when they invest on behalf of third parties.
[25] Bault et al. (2011) and Frydman (2015) present similar results along with neurological evidence.

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 works have also used field data to assess peer effects in financial decisions such as stock market participation (Hong, Kubik, and Stein 2004; Kaustia and Knüpfer 2012) and trading decisions (Kelly and Gráda 2000; Hong, Kubik, and Stein 2005; Shive 2009). For example, Simon and Heimer (2012) 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 payoff in a given period. Yet, we purposefully left aside many of the ingredients which 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, Oechssler, and Weidenholzer 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 Baseline-Feedback than in Baseline. We summarize this conjecture in Hypothesis 1.

Hypothesis 1 (Social feedback)
Bids in Baseline-Feedback will be higher than in Baseline.

3.2. Competition

Beyond social feedback, the Market treatment differs from Baseline 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 that not all bidders can buy the asset. It follows that if traders are unable to purchase the asset, it is because others have outbid them. In 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 the baseline treatments, when traders fail to purchase the asset, they can attribute it to an unusually high random BDM number and not, unlike the Market treatment, to the bidding behavior of other traders.

In line with the *competitive arousal hypothesis* (Ku, Malhotra, and Murnighan 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, Smith, and Walker 1988; Goeree, Holt, and Palfrey 2002; Cooper and Fang 2008; van den Bos et al. 2008). Ku, Malhotra, and Murnighan (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.

Hypothesis 2 (Competition)

Bids in Market will be higher than in Baseline and Baseline-Feedback.

We note that the literature isolating the competition dimension of markets is scant, as we could only identify one paper (Mengel and Peeters 2020) directly comparing a market mechanism with an individual investment task. Mengel and Peeters (2020) aim at studying the causal impact of markets on risk-taking. To that end, they compare 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 their riskiness. When the bids and asks of other participants were displayed in both treatments, Mengel and Peeters report 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, their study uses a complex environment with private information, uncertainty and multiple assets, making it difficult to directly compare their setup with ours.

3.3. Emotions and financial decisions

Numerous works 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) or 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, Odean, and Lin 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 is illustrated by the "calor licitantis" ("bidder's heat"), which under Roman law, protected a bidder who had excessively paid due to bidder's fever (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 the *competitive arousal hypothesis*, we expect that emotional arousal associated with winning bids will be higher in 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, a priori, investors' arousal could also be magnified when not winning the auction, previous research using physiological recordings in gambling tasks has shown limited arousal associated with losing (Wulfert et al. 2005; Coventry and Hudson 2001; Coventry and Constable 1999). In our case, not buying the asset does not result in monetary losses, but rather a zero payoff, thereby leaving investors' earnings unaffected and potentially further limiting any emotional reaction. This is because a prerequisite for any event to produce physiological arousal is to trigger 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 aim to examine, in Hypothesis 3ii, whether this heightened arousal can account for the higher levels of bids in the Market compared to the two baselines 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 alleviate this issue, we study the impact of base rate arousal, measured in the first five periods, on bidding behavior in the 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 Market than in the baseline treatments for traders who exhibit a high base rate level of emotional arousal. In 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 Market than in Baseline and Baseline-Feedback for winning bids but no differences will be observed for non-winning bids.

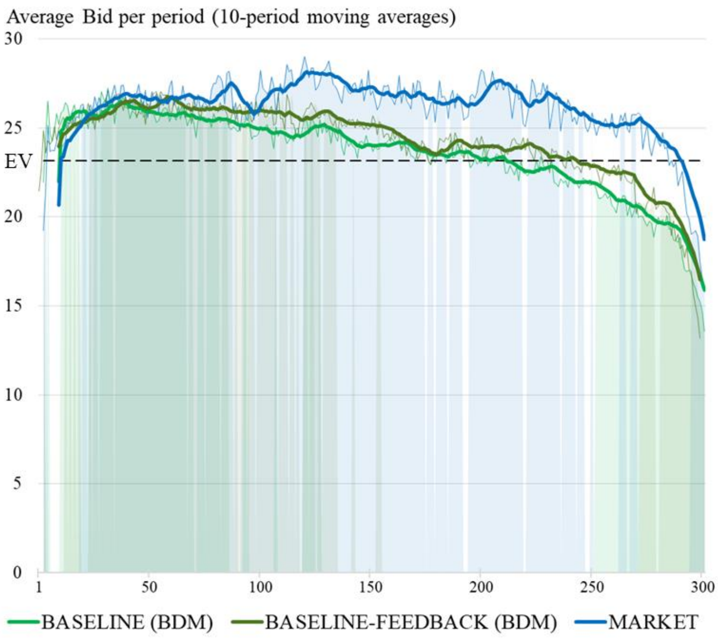
ii) Bidders with a high base rate of emotional arousal will bid higher in Market than in Baseline and Baseline-Feedback whereas no treatment differences will be observed for those with a low base rate.

4. Results

As pre-registered 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 & 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 Figure 1). Even though our setup is one in which all periods are independent so that one cannot retrade the asset in future periods, the Market treatment exhibits a common bubble-crash pattern often found in the experimental bubbles literature (Noussair and Tucker 2013; Palan 2013; Smith, Suchanek, and Williams 1988). In line with previous research on experimental market bubbles, in the Market treatment, bids start below the fundamental value before peaking in the middle of the experiment and crashing toward the end.[26] In contrast, bids decline over time in the Baseline and Baseline-Feedback treatments.



[26] The crash leads to bids that are significantly lower than the expected value in the very last periods (see Figure 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 large.

Figure 1. Average bids per period along with 10-period moving averages (thick lines) across treatments. Colored bands show average bids per period that deviate significantly (at a 1% significance level, Sign Rank Tests) from the expected value for each treatment. Note that expected value (EV = 23.2) is very close to the median bid prediction (23.0) using model simulations from CCH (see Online Appendix II). By construction, participants who went bankrupt could not post subsequent bids so that 5.6% of the bids data is 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, all pairwise comparisons report *p*-values > 0.1).

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 Figure 1, and the non-significant variable 'Treatment Feedback' in Table 2). This leads us to reject Hypothesis 1. In line with Hypothesis 2, bids were 9.1% higher in Market (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 'Treatment Market'). The difference between Market and Baseline-Feedback does not reach significance in regressions (1), (2) and (3) (see Coefficient tests: Market = Baseline-Feedback, lower part of the table) but does so in regression (4). However, the increase in bids in Market compared to both Baseline and Baseline-Feedback treatments combined is significant (see Market = Baseline-Combined, lower part of Table 2).

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 in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize 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*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. †Baseline-Combined is a dummy variable taking value one if a person is 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 value 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) (Online Appendix 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 (5.6% of the data). We used 1,000 replications for the bootstrapped standard errors.

In Figure 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 (see blue colored 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 Market compared to 25.3% and 36.7% for Baseline and Baseline-Feedback (Proportion tests comparing Market and each of the two baseline treatments, *p*-values < 0.001).

To study dynamics, we fit bids using a quadratic trend in Table B1 (Internal Appendix B.1). We find evidence of a bubble-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 Figure 1, the anatomy of the bubble-crash pattern is 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. At its peak, overpricing was thus equal to 20.1% of the expected value of the asset in Market compared to 11.2% and 13.0% in Baseline and Baseline-Feedback. These results indicated that the amplitude of the bubble is more pronounced in Market than in the two baselines.

Result 1. (Bids, bubbles and Competition)

i) Bids were significantly higher in Market than in the two baseline treatments.

ii) Bids exhibited a more pronounced bubble pattern in Market than in the two baseline treatments.

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* (Ku, Malhotra, and Murnighan 2005). This hypothesis suggests that rivalry and the "joy of winning" (Malhotra, 2010) 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 the 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.[27]

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

We start 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 Market than in the two baseline treatments. In Figure 2, we show that emotional arousal is consistently higher after a winning bid in Market, while this is not the case in the two baseline treatments. In Market, investors showed on average an emotional reaction to winning bids in 27.8% of the cases compared to 20.2% for other bids. For Baseline [Baseline-Feedback], the difference in emotional reaction was less pronounced (23.3% vs 21.8%) [25.0% vs 20.9%].

[27] 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.

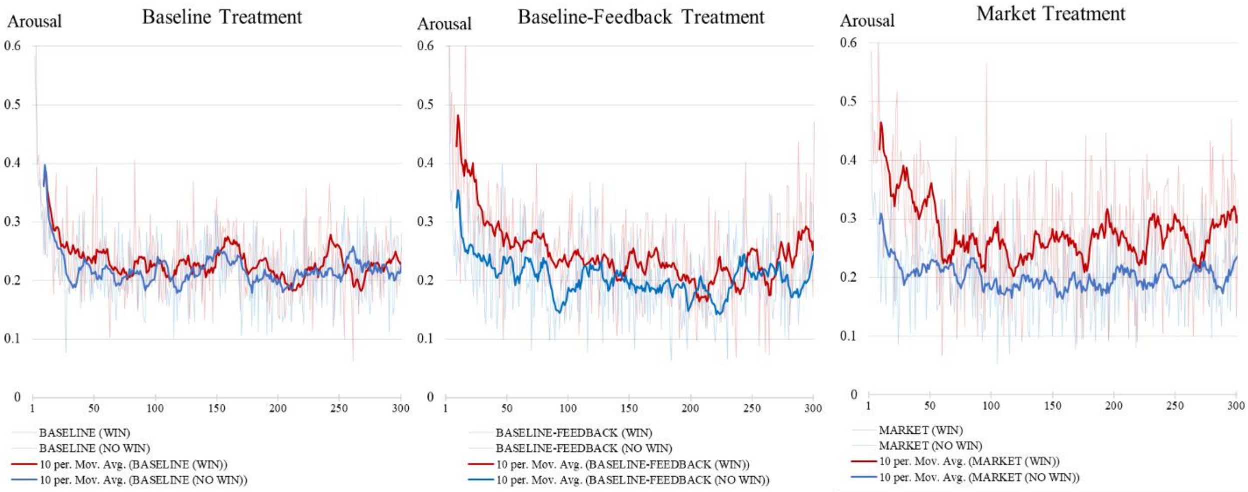


Figure 2. Proportion of investors who showed emotional arousal after observing feedback in a given period and across treatments. Red (blue) curves correspond to cases in which the investor bought (did not buy) the asset. We show the periods in which the payoff of the asset was positive (99.2% of the data).[28]

In Table 3, we show that these differences in emotional reaction to winning bids were significantly higher in Market than in Baseline. 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 yet non-significant and about ten times smaller than the coefficient for 'Market × Win'. The higher emotional reaction due to winning in Market than in Baseline-Feedback is significant in all regressions (see Coefficient tests: Market × Win = Baseline-Feedback × Win, lower part of the table). In contrast, 'Market' and 'Baseline-Feedback' are not significant thus showing that no differences in arousal exist for non-winning bids between these two treatments and Baseline. Furthermore, the coefficient test for 'Market = Baseline-Feedback' cannot be rejected so that there is no significant difference in arousal between these two treatments for non-winning bids.

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-value < 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 so that they are orthogonal to bids. In Market, prices are determined by an auction and are thus a

[28] In CCH, we study the physiological reaction of traders to large losses in the Baseline treatment only. In that case, the emotional reaction to buying the asset is unambiguously negative.

function of bids in a given period so that, unsurprisingly, individual bids correlate positively with prices ($\rho = 0.326$, p-value < 0.001). To alleviate this issue, we can construct an alternative variable 'Price$^{\perp}$' that is orthogonal to bids regardless of the treatment.[29] This variable is thus uncorrelated with bids while correlating significantly with 'Win' ($\rho = 0.687$, p-value < 0.001). In Table B2 in Internal Appendix B.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 Market. We examine our hypothesis in more detail by inquiring on the valence of emotion, thus complementing our physiological arousal measure.

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 in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive 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 included). (std) stands for standardize variables.

DEPENDENT VARIABLE	(1)	(2)	(3)	(4)
	Arousal Dummy			
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

[29] We construct this variable using the orthog command in Stata 17.0.

		(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

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Win is a dummy that takes value 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.

In Table 3, we excluded the 0.8% of observations associated with negative payoffs.[30] This was done because these large negative payoffs trigger a specific emotional reaction unrelated to competitive arousal and that was studied in CCH for the case of Baseline.[31] The authors showed that arousal was linked to anger when investors bought the asset, and the payoff was -1,000. Unsurprisingly, using data collected for Baseline-Feedback, we found that people did not report an anger response when buying the asset when payoffs were positive (see Table B3 in Internal Appendix B.2).[32]

Out of the four basic valenced emotions (fear, anger, joy and sadness, Ekman 1992), only joy was reported as a prominent emotion in the case of buying the asset and when the payoff was equal to its maximum possible value of 50.[33] In that case, the participants reported feeling “Very much” joy and “Not at all” anger, fear or sadness. The “joy” emotion was thus more intense when buying the asset than any of the other emotions (Sign Rank Tests, all *p*-values < 0.001). When not buying the asset, all reported emotions were of low intensity and significantly lower than the midpoint in the Likert scale. Yet, “sadness” was the most intense emotion (Sign Rank Tests, all *p*-values <

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

[31] Not only is the valence of the emotion, as explained in the text, different but also the magnitude of the response. The average for the ‘Arousal Dummy’ was 56.6% compared to 22.7% for the other payoffs with no major differences across treatments.

[32] 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.

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

0.005). This indicates a “pain of losing” effect associated with non-winning bids, which is the counterpart of the “joy of winning” effect. However, the “pain of losing” effect was of lower magnitude than the “joy of winning” (Sign Rank Test for the difference in difference, p-value < 0.001). Overall, people reported being more joyful and less sad after a winning than after a non-winning bid. Interestingly, the self-reported emotional intensity associated with the end-of-experiment questionnaire was overall in line with physiological arousal (see Figure B1 in Internal Appendix B.2).

The case of a payoff of 50 is one in which winning bids cannot be associated with monetary loss given that the maximum bid is 50. In contrast, winning bids were most of the time (65.1%) 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 as the “joy of winning” is mitigated 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, all p-values < 0.001) (see right panel of Table B3 in Internal Appendix B.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 (Sign Rank Tests, all p-values < 0.001) when the payoff was 10. 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-value < 0.001). Second, although winning bids were most of the time (65.1%) associated with a monetary loss when the asset payoff was 10, they were overall mostly associated with monetary gains (76.4%).

In Figure B2 in Internal Appendix B.2, we show that arousal was higher in Market than in the two baseline treatments when asset payoffs were high (40 or 50) whereas it was not necessarily the case for low payoffs (10 or 20). In Table B4 in Internal Appendix B.2, we show that the increase in arousal in Market is indeed exacerbated 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 Market after winning bids thus also captures the “joy of money”, which could reflect heightened greed in markets (Seuntjens et al. 2014; 2015). This is confirmed in Table B5 (Internal Appendix B.2) in which we show 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". In Table B4, we show that low payoffs (10 or 20) defined as being below the median payoff of 30 lead to a winning bid arousal as the coefficient 'Market × Win' is positive and significant. This occurs even though investors make monetary losses in half of the cases (49.0%) compared to 0.7% for high payoffs (40 or 50). Yet, one notices that the coefficient for the impact of winning bids with high payoffs is twice higher than under low payoffs (Coefficient tests: 'Market × Win × High Payoff = Market × Win', all regressions *p*-values > 0.1). However, Table B6 shows that there exists an emotional reaction due to winning bids in the absence of monetary gains, which is captured by the interaction term 'Market × Win' that is 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 B6.

In Result 2, we summarize our findings regarding our test of Hypothesis 3i.

Result 2. (Arousal across treatments)
i) Investors were substantially more aroused after winning bids in Market than in the two baseline treatments.
ii) No treatment differences in arousal were observed after non-winning bids.
iii) Only a small fraction of the arousal associated with winning bids can be attributed to monetary gains.

4.2.2. Hypothesis 3ii (Base rate arousal)

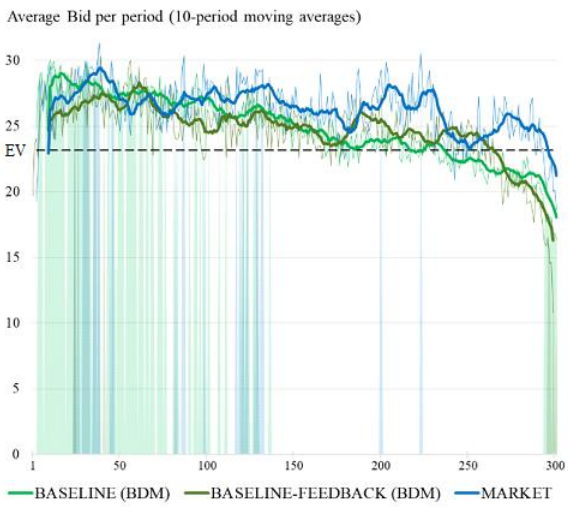
We proceed to testing Hypothesis 3ii according to which bids are higher in Market than in the two baseline treatments due to an increased level of arousal in this treatment. To avoid endogeneity issues when measuring the impact of emotional arousal on bidding behavior, we use a measure of base rate arousal, 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.[34] An investor is then classified as having low (high) base rate arousal when its level is below (above) the median of 2. By definition, base rate arousal could potentially 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 (ρ = -0.014, *p*-value = 0.788). Furthermore, we

[34] The cited authors used a 5-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.

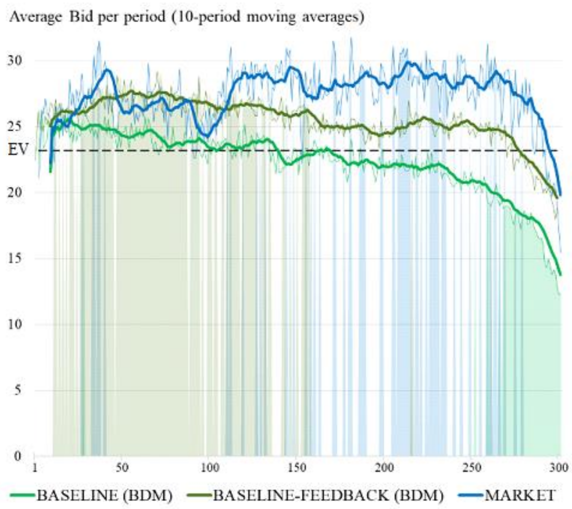
observe only small differences in base rate levels across treatments. The Market treatment actually shows a slightly lower base rate arousal (39.5%) than the Baseline (46.9%) and Baseline-Feedback (47.7%) treatments although not significant differences emerge (Rank Sum Tests, *p*-values = 0.073, 0.058, and 0.830 when comparing Market and Baseline, Market and Baseline-Feedback, and the two baselines). 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. The rate of arousal is indeed twice higher in the first five periods than in subsequent periods (45.3% vs 22.6%, Rank Sum Test, *p*-value < 0.001).

As expected, investors with a high base rate arousal exhibited a more frequent emotional response to winning bids in subsequent periods than those with a low base rate (35.0% vs 15.8%, Rank Sum Test, *p*-value < 0.001). Furthermore, as expected, investors with a high base rate arousal showed a more frequent emotional response to subsequent winning bids in Market (44.1%) than in the Baseline (32.3%, Rank Sum Test, *p*-value = 0.006) and Baseline-Feedback treatments (33.7%, Rank Sum Test, *p*-value = 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*-value = 0.199) [18.7% vs 14.5%, Rank Sum Test, *p*-value = 0.299].

In line with Hypothesis 3ii, we observe that investors who had a low level of base rate arousal, defined as being below the median of 2, exhibited limited differences in bidding behavior across treatments (see left panel in Figure 3). In 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 Figure 3).



Low base rate arousal investors



High base rate arousal investors

Figure 3. Average bids per period along with 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. Colored bands show average bids per period that deviate significantly (at a 1% significance level, Sign Rank Tests) from the expected value (EV = 23.2) for each treatment. By construction, participants who went bankrupt could not post subsequent bids so that 4.4% (6.9%) of the bids data is 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*-value = 0.048).

In Tables B7 and B8, we replicate the regression analyses in Table 2 for low and high base rate arousal investors. In line with Figure 3, we find that the significant increase in bids in Market compared to Baseline only emerges for investors with a high base rate arousal (see 'Market' in Table B8). This finding is consistent with Hypothesis 3ii and is summarized in Result 3.

As shown in Figure 3, bids in Baseline-Feedback for investors with a high base rate arousal are in between Baseline and Market. Actually, bids in Baseline-Feedback are significantly higher than in Baseline in regressions (1) and (3) while not being significantly lower than Market in any of the regressions (see 'Baseline-Feedback' in Table B8). This suggests feedback about others' bids might also have increased the "joy of winning" for investors who have a high base rate arousal level. This result shows that investors who have a high base rate level of arousal are also likely to respond to the presence of feedback by increasing their bids.

Result 3. (Bids and base rate arousal)
i) Bids were not significantly different across treatments for those who exhibited a low base rate arousal.
ii) Bids were significantly higher in Market than in Baseline for investors who exhibited a high base rate arousal but not significantly higher in Market than in Baseline-Feedback.

4.2.3. Exploratory analysis: earnings and bankruptcy rates

We have already shown that Market tends to produce higher bids than the two baseline treatments, especially for those investors who exhibit a high level of base rate arousal. This implies that average bids are also higher than the expected value of the asset in Market 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 Market than in the baseline treatments (see Figure 4, upper panel).

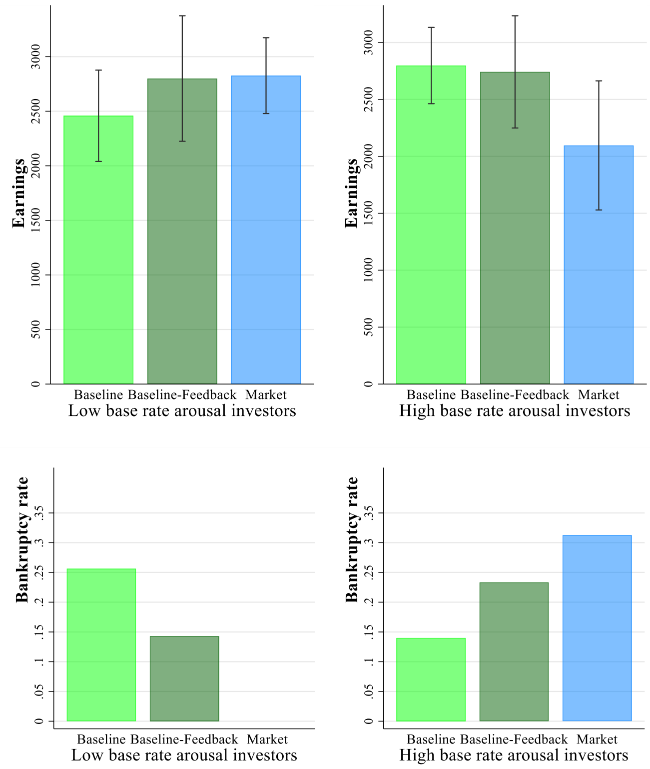


Figure 4. Average earnings (bankruptcy rates) across treatments for low (high) base rate arousal investors on the left (right) panel for sessions in which bankruptcies were possible, that is characterized by the occurrence of at least two negative payoffs. 95% confidence intervals included for earnings (not included for bankruptcy rates which are simple proportions).

Higher bids in Market are also associated with a higher risk of facing a large negative payoff during the experiment. In sessions in which investors faced two of these negative payoffs, they could go bankrupt. Focusing on these sessions (68.9% of the data), we observe that for high base rate arousal investors the frequency of bankruptcies was higher in Market (31.3%) than in Baseline (14.0%) and Baseline-Feedback (23.3%) (see Figure 4, lower panel). Interestingly, the reverse ordering of treatments was observed for low base rate arousal investors. This implies exhibiting low base rate arousal especially protects investors from bankruptcy in a market setup.

We show the statistical significance of these differences in Tables B9 and B10 in Internal Appendix B.3. In Table B9, we show 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 in Market compared to Baseline. These regressions consider the sessions where 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 so that base rate arousal is not detrimental in Baseline-Feedback compared to Baseline. Although the magnitude of the coefficient for ‘Market × Base rate arousal’ is about two to three times larger, depending on the regression, than ‘Baseline-Feedback × Base rate arousal’, we report no significant differences between these two interaction terms (see Coefficient tests at the bottom of Table B9). In Market, the estimates in Table B9 show that for an investor with a median level of base rate arousal, equal to 2, the decrease in earnings ranges from to 3.29 to 5.58 euros for a 3-hour experiment, which corresponds to about 10% of their earnings for the experimental session.[35]

In Table B10, similar results are obtained when considering bankruptcy rates so that base rate arousal was associated with more frequent bankruptcies in Market compared to Baseline (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 B10 for regressions (3) and (4)). This shows that, when considering bankruptcies, base rate arousal was also detrimental to traders in Market when compared to Baseline-Feedback.

We summarize our findings regarding earnings and bankruptcies in Result 4.

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

In Market, investors with a high base rate arousal were more likely to go bankrupt and earned less in sessions where bankruptcy was possible than those with a low base rate arousal. No differences between these two groups were observed for the baseline 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 (Bechara et al. 1997; Damasio 1996; Bechara and Damasio 2005). In particular, recent research using experimental markets has shown that anticipatory arousal, possibly reflecting fear and anxiety, is

[35] This decrease in earnings in Market for a base rate arousal equal to 2 is calculated as 2×‘Base rate arousal’ + 2×‘Market×Base rate arousal’, which leads to the following estimates of -3.29, -3.36,-5.58 and -5.42 in regressions (1) to (4).

associated with higher earnings because it helps investors avoid excessive risk (Bossaerts et al. 2023; Corgnet, Cornand, and Hanaki 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 Figure O3 and Table O2 in Online Appendix III), even when considering the interaction term between treatment dummies and winning bids in the previous period (Table O3). It follows that the increase in bids in Market compared to the baseline 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 competition, 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 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, thus leading 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, Sazma, and Yonelinas 2016). However, we believe learning plays a limited role in our 300-period experiment.

In the survey conducted before the experiment, we elicited investors' estimates of the percentage 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 true value of 19.9% [0.67%] (Sign Rank Test, p-value = 0.006) [p-value < 0.001]. This implies that 71.8% of the investors overestimated the probability of 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 as bids sharply increased in the early periods, especially in the Market treatment (see Figure 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, Harstad, and Levin 1987; Georganas, Levin, and McGee 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 Online Appendix I.1), a strong predictor of bias avoidance (Oechssler and Schmitz 2009; Toplak, West and Stanovich 2011; Meyer et al. 2024). While investors scoring above the median on the test bid lower (with an average bid of 21.37¢ and a median bid of 22.0¢) than those below the median (with respectively 22.66¢ and 23.0¢), their bids in the Market remain higher (22.66¢ and 25.0¢) compared to Baseline-Feedback (20.33¢ and 21.0¢) and Baseline (21.30¢ and 21.0¢) (Rank Sum Tests, p-values < 0.001).[36]

5.2. Anticipated emotions

Our interpretation of the *competitive arousal hypothesis* has been that the experienced arousal following winning bids leads investors to subsequently increase their bids out of a current state of excitement. Yet, 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 role of anticipated emotions. However, our findings shed some light on the interaction between anticipated and experienced emotions. In particular, Figure 1 shows that bids in Market are very close to those in the two baselines in the first 50 periods. In fact, the discrepancy between bids in the Market and baseline treatments progressively increases over time, as shown by the positive and significant term 'Period × Market' in regression Table B11 (see Appendix B3). Our findings thus demonstrate that investors do not immediately bid at higher values in Market 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),

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

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). In 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 US, thereby limiting the role of spiteful behavior.

5.4. Attention

The critical difference between the Market treatment and the 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. The Market treatment may sustain a higher level of trader engagement compared to 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 Market (6.6%) than in the baselines (2.1%) suggesting participants were not less attentive and engaged in the baseline treatments (see Figure B3). 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 ten periods to up to 8.2% in period 100 (see Figure B3). However, the regression results in Table B12 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. These results continue to hold when considering separately investors who exhibited low and high base rate arousal (see Table B13).[37]

5.5. Rare losses

[37] Our second measure, decision arousal, also shows that there is no differences between treatments (see Figure B3 and Tables B12 and B13).

One may 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 (Hertwig et al. 2004), could explain the observed treatment differences. Indeed, as is shown in Table 2 (see also CCH), rare losses incurred in the previous period led to higher bids. However, this effect of rare losses does not differ significantly across treatments, as shown in Table B14, 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 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 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 B15).

Finally, one may 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 B16 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 the main 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 Online Appendix II), differences across treatments may arise because deviating from this strategy might be more tempting in Market. In the Market treatment unlike in the baselines, highly risk-averse investors will be unable to accumulate earnings if they bid their value because 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 staying engaged in the experiment. This behavior could potentially help explain the larger increase in bids in Market 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.[38] We also consider an alternative measure that accounts for an investor's relative risk aversion within their experimental group, which we refer to as 'Rank Risk'. This relative measure of risk aversion is a dummy variable that takes value one if a person is the most risk-averse person in their group (11.8% of the people in our sample).[39]

Regardless of the measure used and at odds with the proposed explanation, the increase in bids in Market compared to the baselines (see Table 2) was not more pronounced for the subset of highly risk-averse investors as is shown in Tables B17 and B18 (see 'Market × High Risk Aversion Dummy' and 'Market × Rank Risk' which are not significant and 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, the heightened arousal after buying the asset in Market (see Table 3) was not more pronounced, regardless of the measure, for the subset of highly risk-averse investors as is shown in Tables B19 and B20 (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 models used in CCH show no differences across treatments, the increase in bids in Market compared to Baseline could potentially be explained by loss aversion, assuming a sufficiently high reference point. Indeed, in CCH models, the reference point was fixed at the actual wealth level, which is an investor's endowment of 1,200¢. 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. Indeed, as the reference point increases to 1,700¢ and 2,200¢, 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 1,200¢ in both Market and Baseline (see Figure B4). Interestingly, the increase in bids is more pronounced in Market than in Baseline, as investors remain in the loss domain for longer, thus triggering more risk-seeking behavior. In the Baseline

[38] 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), as described by Holt and Laury (2002) as very risk-averse.
[39] Similar results hold if we consider the two most risk-averse people in the group (28.4% of the people in our sample).

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 (2,700¢), bids increase substantially in Baseline as investors remain in the loss domain for longer, ultimately converging to the levels observed in Market.

For intermediate values of the reference point, loss aversion can thus explain the dynamics in bids in Market and Baseline 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 Market than in Baseline. However, prospect theory falls short of explaining the level of bids, which in Market is about 25% higher on average than the asset 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 Market. It also fails to account for why differences across treatments tend to disappear for investors who exhibit low base rate arousal. We 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 the competition among investors.

6. Conclusion

Our study is the first to provide causal evidence that markets trigger specific emotions. These emotional responses, unique to the market institution, are characterized by investors experiencing heightened emotional arousal when outcompeting other traders. Interestingly, the exacerbated emotional response to winning bids in markets was more pronounced when asset payoffs were high. This suggests 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, namely competition, 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 as it exacerbates emotions and induces lower gains due to a higher risk of bankruptcy.

Interestingly, competitive arousal induces aroused traders to bid at higher levels while not impacting their unaroused counterparts thus creating heterogeneity in bidding behavior. These heterogenous reactions could, in a market in which speculation is possible, further facilitate the development of bubbles since even the less aroused traders will be willing to bid high to resell to aroused traders. This mechanism relates to behavioral models of speculative bubbles in which traders are assumed to hold heterogenous beliefs due to overconfidence over the asset value (Abreu and Brunnermeier 2003; Scheinkman and Xiong 2003; Hong, Scheinkman, and Xiong 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 (Kandasamy et al. 2016; Astor et al. 2014) 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 consists in redesigning existing institutions. Doing so can reduce competitive arousal without necessarily impacting other emotional responses that are necessary to make successful investment decisions.

Because we wanted to compare our Market treatment with non-market baselines, we 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 (see Bao et al. 2022; Asparouhova et al. 2024; Corgnet, DeSantis and Siemroth 2024).

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Appendices

INTERNAL APPENDIX

The Internal Appendix is organized as follows:

A. Instructions (Part 2, investment task) and Post-experimental Questionnaire on Emotions

B. Robustness of results

Appendix A: Instructions (Part 2 investment task) and questionnaire on emotions

A.1. INSTRUCTIONS FOR PART 2 (*COMMON TO THE 3 TREATMENTS; UNLESS OTHERWISE STATED INSTRUCTIONS ARE FOR THE BASELINE TREATMENT*)

Oral instructions; *Sentences in italics are for the readers and not shown to participants.*

In this second part, we are carrying out the experiment itself.

Here is a bow of tokens. *After the experimenter has shown the box, he tells the participants:* We will take a picture that will be reported on your screen to remind you the contents of the box.
The experimenter takes a photograph that is supposed to resemble the one depicted on participants' screens later on.

Instructions - PART 2 ON SCREEN

During preceding experimental sessions, 15 participants have been randomly selected to perform the following task:
- put all the chips in an opaque bag;
- pick a token from the bag, tick the color of the token on his/her computer screen;
- tick the color of the token on the sheet of paper in front of him/her;
- put the token back into the opaque bag (so that the contents of the bag always remains the same), mix the tokens;
- and again pick a token from the bag, tick the color of the token on his computer screen, tick the color of the token on the sheet of paper;
- put the token back in the bag, mix the tokens, and so on until you have drawn a total of 300 tokens;
- sign the sheet of paper at the end of his/her task.

Each selected participant was paid a fixed amount of 15 euros to complete this task in an hour. None of these participants knew your own task of the current experiment.

15 draws of 300 tokens have thus been realized in total and one of these draws will be randomly selected for the current experiment.

Instructions

You are divided into groups of 6 participants.

We will now proceed to the selection of one of these 15 draws for each group of 6 participants.

We assigned a number to each of the 15 draws, written on the back of the sheets signed by the participants who picked up the tokens.

For each group of 6 participants, a randomly selected participant will have to choose a number between 1 and 15 on his screen. All numbers between 1 and 15 can be chosen, except those already drawn in other sessions identical to yours or in this session by other participants in another group than yours. This number will be communicated on your screen.

At the end of the experiment, if you wish, you will be able to consult the sheet of paper signed by the participant who drew the tokens and who was randomly selected by this procedure. You will be able to check that this sheet of paper is the correct one to be selected by matching its number with the one given to you on the screen and to verify that the sequence of tokens drawn is correct.

Your task:

You will play for 300 periods.

At each period, your task is to decide how much you are willing to pay for a lottery that gives you the following payoffs (which may be negative) depending on the color of the token drawn by the randomly selected participant:

- Blue: 10 cents
- Red: 20 cents
- Orange: 30 cents
- Green: 40 cents
- Purple: 50 cents
- Yellow: -1000 cents

The outcome of the lottery in one period is independent of the outcome of the lottery in another period: in each period a new token is drawn into the bag which has strictly the same content in each period.

To make your decisions, you will use the fixed amount of 12 euros (1200 cents) that you were attributed to answer the tests during the first part of this experimental session.
This initial endowment is intended both to allow you to pay the lottery and to deal with the possibility of a yellow token being drawn. The earnings for each period are added to this initial endowment.
In addition, we make you a loan of 10 euros (1000 cents) for liquidity reasons, which you will repay at the end of the experiment.
If your endowment is no longer sufficient to cover the actual occurrence of a yellow token, you will no longer be able to participate in the experiment and you will only earn your variable payoffs acquired during the tests as well as 5 euros for showing-up.

You can select on your screen any price between 0 and 50 cents up to which you would be willing to buy the lottery.
The computer randomly selects an integer from 1 to 50.
If the price you indicate is greater than or equal to the number selected by the computer, then you buy the lottery for the price equal to the number selected by the computer.
If the price you indicate is strictly lower than the number selected by the computer, then you keep your endowment and do not buy the lottery.
At each period, your payoff, if you actually buy the lottery, is given by:
Lottery payoff - price paid to purchase the lottery
Your total earnings over the 300 periods are given by:

1200 cents of fixed test earnings + (lottery payoff - price you paid to buy the lottery) × 300 periods + variable test earnings + 5 euros of show-up fee.

In the case of MARKET TREATMENT, this screen was:

Your task:

You can select on your screen any price between 1 and 50 cents up to which you would be willing to buy the lottery.

The computer randomly selects the price proposed by one of the participants.
If the price you indicate is strictly greater than the price selected by the computer, then you buy the lottery for the price equal to the number selected by the computer.
If the price you indicate is lower than or equal to the number selected by the computer, then you keep your endowment and do not buy the lottery.
At each period, your payoff, if you actually buy the lottery, is given by:
Lottery payoff - price paid to purchase the lottery
Your total earnings over the 300 periods are given by:
1200 cents of fixed test earnings + (lottery payoff - price you paid to buy the lottery) × 300 periods + variable test earnings + 5 euros of show-up fee.

Example 1
You have entered a price of 28 at which you are ready to buy the lottery.
The computer randomly selects between 1 and 50 the number 12. In this case, the price you have indicated is higher than the selected number, so you buy the lottery for 12 cents that corresponds to the number selected by the computer. This lottery will give you:

- 10 cents if the token drawn is blue, in which case your payoff for this period is -2 cents (10-12).
- 20 cents if it is red, in which case your payoff for this period is 8 cents (20-12).
- 30 cents if it is orange, in which case your payoff for this period is 18 cents (30-12).
- 40 cents if it is green, in which case your payoff for this period is 28 cents (40-12).
- 50 cents if it is purple, in which case your payoff for this period is 38 cents (50-12).
- -1,000 cents if it is yellow, in which case your payoff for this period is -1012 cents (-1000-12).

In the case of MARKET TREATMENT, this screen was:

Example 1
You have entered a price of 28 at which you are ready to buy the lottery.
The computer randomly selects the price proposed by one of the participants which is equal to 12. In this case, the price you have indicated is strictly higher than the selected number, so you buy the lottery for 12 cents that corresponds to the number selected by the computer. This lottery will give you:

- 10 cents if the token drawn is blue, in which case your payoff for this period is -2 cents (10-12).
- 20 cents if it is red, in which case your payoff for this period is 8 cents (20-12).
- 30 cents if it is orange, in which case your payoff for this period is 18 cents (30-12).
- 40 cents if it is green, in which case your payoff for this period is 28 cents (40-12).
- 50 cents if it is purple, in which case your payoff for this period is 38 cents (50-12).
- -1,000 cents if it is yellow, in which case your payoff for this period is -1012 cents (-1000-12).

Example 2
You have entered a price of 21 and the computer randomly selects between 1 and 50 the number 43.
In this case, the price you have indicated is lower than the selected number, so you will not buy the lottery.
In this case, your payoff is 0 for this period.

In the case of MARKET TREATMENT, this screen was:

Example 2
You have entered a price of 21 and the computer randomly selects the price proposed by one of the participants which is equal to 43.
In this case, the price you have indicated is lower than the selected number, so you will not buy the lottery.
In this case, your payoff is 0 for this period.

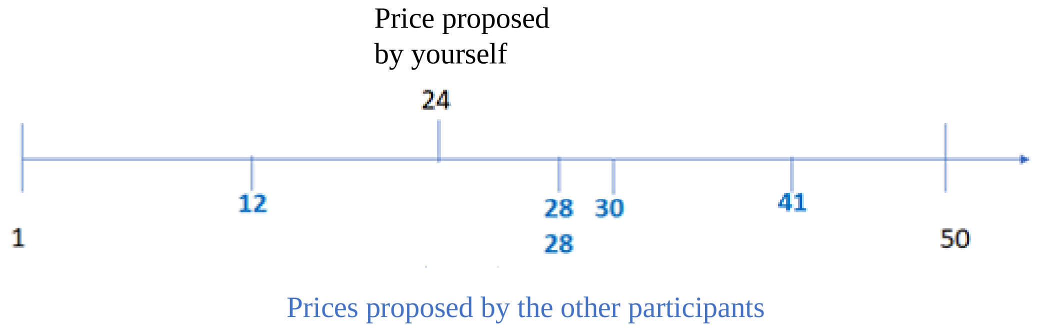
Information:
After each period, you will be informed about the token that has been drawn, your payoff for the lottery, as well as your available cash which is equal to your initial endowment (2200 cents) plus or minus the accumulated gains and losses for buying (or not) the lottery.
You will also be able to see this information at the bottom of your screen for all periods before the current period.

At the end of the experiment, if you wish, you can have a look at the sheet of paper signed by the participant who drew the tokens. This will allow you to check that the sequence of drawn tokens is correct.

In the case of FEEDBACK AND MARKET TREATMENTS, this screen was:

Information:

After each period, you will be able to observe for 4 seconds the prices offered by the other participants and their relative position in relation to your own price proposal by means of a simple graph. An example is shown below where you have proposed a price of 24 while the other five participants have proposed the following prices: 12, 28, 28, 30 and 41.



On the next screen, you will be informed about the token that has been drawn, your payoff for the lottery, the price that you have offered, the average price offered by the other participants as well as your available cash which is equal to your initial allocation (2200 cents) plus or minus the accumulated earnings and losses.

You will also be able to see this information at the bottom of your screen for all periods prior to the current period.

Decision-making time:
To ensure that the experiment is completed on time, we expect you to make your decision within 10 seconds in each period.
Note that you can take a little more time at the beginning of the experiment and that you are expected to make your decisions more quickly over time.
You are given 30 seconds in the first period and 20 seconds in the second period.
From the third period onwards, you will have 10 seconds to make your decision. A timer on the screen will indicate the time you have to enter a price using the cursor and validate your decision. If you do not enter a price on the screen and validate your decision in time, the number indicated by the cursor will be selected.

A.2. POST-EXPERIMENTAL QUESTIONNAIRE ABOUT EMOTIONS FOR Market physio, Baseline-Feedback physio AND HALF OF DATA OF Baseline physio

The order of the two following questions was randomized.

(Q1) When the yellow token was drawn during the experiment and you suffered a loss of 1,000 euro cents, how much did you feel the following emotion? Anger, Fear, Joy, Sadness (1- Not at all 2- A little 3- Moderately 4- Very much 5- Very much)

(Q2) When the yellow token was drawn during the experiment, but you did not suffer a loss of 1,000 euro cents, how much did you feel the following emotion? Anger, Fear, Joy, Sadness (1- Not at all 2- A little 3- Moderately 4- Very much 5- Extremely)

We also randomized the order of presentation of each emotion.

A.3. ADDITIONAL POST-EXPERIMENTAL QUESTIONNAIRE ABOUT EMOTIONS FOR Baseline-Feedback physio SESSIONS

The order of the following questions was randomized two by two on (Q3) and (Q4) on the one hand and (Q5) and (Q6) on the other.

(Q3) When the blue token (payment of 10 cents) was drawn during the experiment and you bought the lottery, did you feel the following emotion? Anger, Fear, Joy, Sadness (1- Not at all 2- A little 3- Moderately 4- Very much 5- Very much)

(Q4) When the blue token (payment of 10 cents) was drawn during the experiment and you did not buy the lottery, did you feel the following emotion? Anger, Fear, Joy, Sadness (1- Not at all 2- A little 3- Moderately 4- Very much 5- Very much)

(Q5) When the purple token (payment of 50 cents) was drawn during the experiment and you bought the lottery, did you feel the following emotion? Anger, Fear, Joy, Sadness (1- Not at all 2- A little 3- Moderately 4- Very much 5- Very much)

(Q6) When the purple token (payment of 50 cents) was drawn during the experiment and you did not buy the lottery, did you feel the following emotion? Anger, Fear, Joy, Sadness (1- Not at all 2- A little 3- Moderately 4- Very much 5- Very much)

We also randomized the order of presentation of each emotion.

Appendix B: Robustness of the results

B.1. Hypotheses 1 & 2

Table B1. Bids and quadratic trend fitting.

Treatment	Baseline	Baseline-Fedback	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)
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*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. † This 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 value one if a participant was assigned to the Market (Baseline-Feedback) treatment.

B.2. Hypothesis 3

Table B2. Arousal dummy and winning bids (IV regression). Instrumental variable panel regressions with random effects along with robust standard errors in parentheses. Instrument used for 'Win' is 'Price$_\perp$'. (std) stands for standardize variables.

	(1)	(2)
DEPENDENT VARIABLE	Arousal Dummy	
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*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Win is a dummy that takes value one if a participant bought the asset in a given period. Negative payoffs periods are excluded from the analysis (99.2% of the data 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.

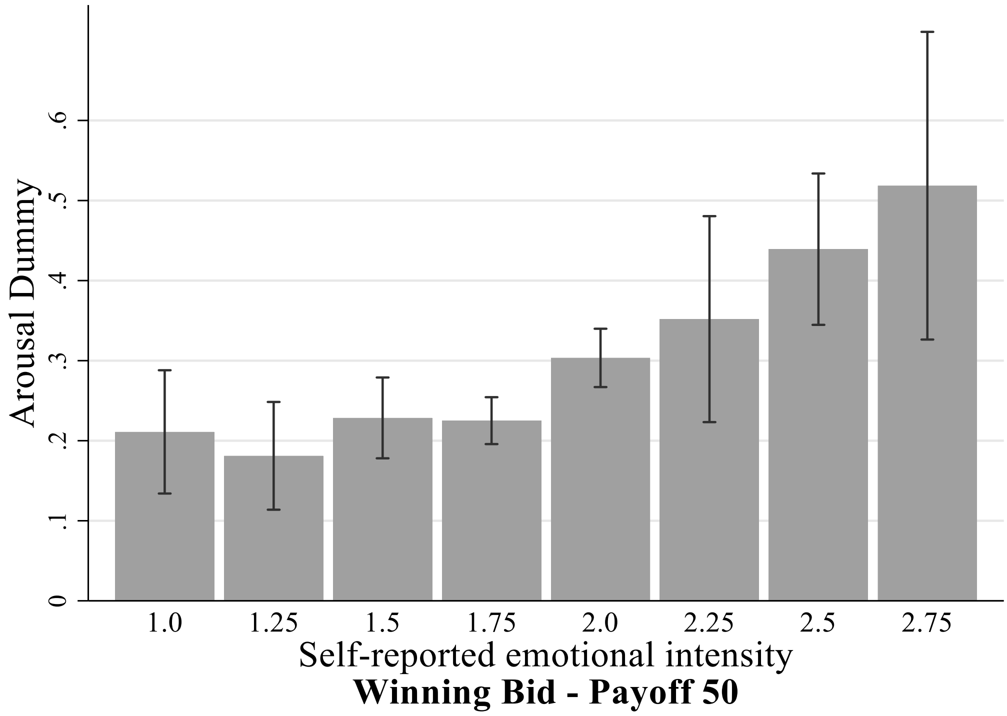


Figure B1. Arousal Dummy as a function self-reported emotional intensity for the case of a payoff of 50 and a winning bid. Self-reported emotional intensity was calculated as the average Likert scale answer on the four basic emotions for the case of winning bid and a payoff of 50.

Table B3. Emotion reported by participants at the end of the experiment (Baseline-Feedback treatment) for the four basic valenced emotions after a winning and a non-winning bid. Only participants who effectively placed a winning (non-winning) bid for a given payoff were asked to report their emotion. Mean (median) responses for a Likert scale ranging from 1 “Not at all” to 5 “Extremely”. SD stands for standard deviation. In brackets, we also report Sign Rank Tests *p*-values [p] for the hypothesis that the reported emotion is moderate (Answer 3 in the 5-point Likert Scale).

Payoff 50	Winning Bid	Non-Winning Bid
Anger	1.10 (1.00) SD = 0.43 [p < 0.001]	2.02 (2.00) SD = 1.12 [p < 0.001]
Fear	1.22 (1.00) SD = 0.58 [p < 0.001]	1.18 (1.00) SD = 0.52 [p < 0.001]
Joy	3.81 (4.00) SD = 1.10 [p < 0.001]	1.18 (1.00) SD = 0.62 [p < 0.001]
Sadness	1.03 (1.00) SD = 0.18 [p < 0.001]	2.39 (2.00) SD = 1.12 [p < 0.001]

Payoff 10	Winning Bid	Non-Winning Bid
Anger	1.67 (1.00) SD = 0.92 [p < 0.001]	1.28 (1.00) SD = 0.64 [p < 0.001]
Fear	1.41 (1.00) SD = 0.71 [p < 0.001]	1.18 (1.00) SD = 0.61 [p < 0.001]
Joy	1.53 (1.00) SD = 0.80 [p < 0.001]	2.06 (1.00) SD = 1.18 [p < 0.001]
Sadness	1.76 (2.00) SD = 0.88 [p < 0.001]	1.34 (2.00) SD = 0.75 [p < 0.001]

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

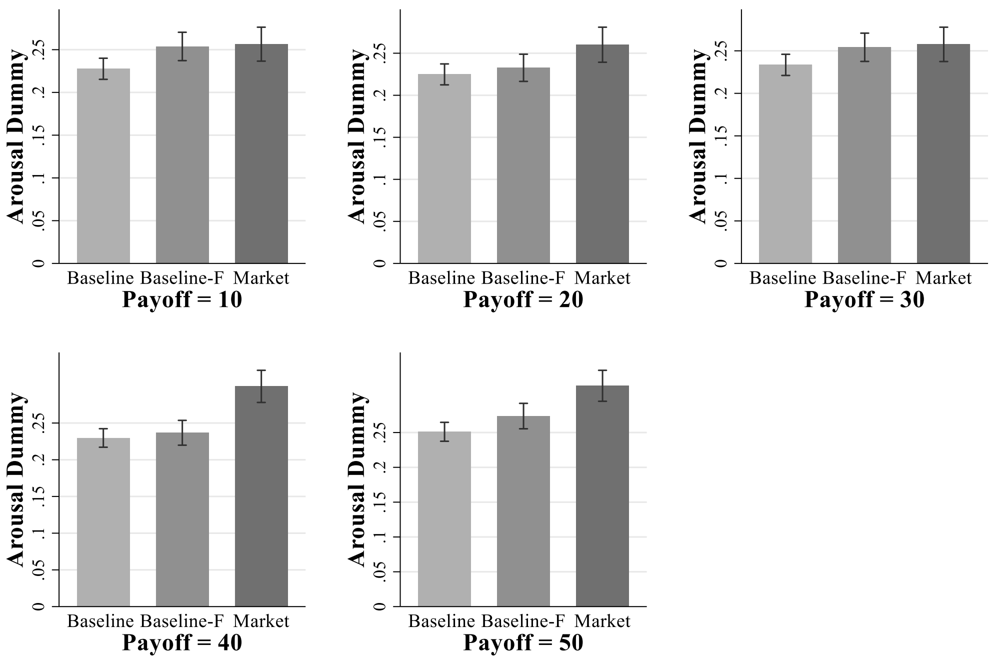


Figure B2. Emotional arousal for winning bids across treatments and asset payoffs. “Baseline-F” stands for Baseline-Feedback.

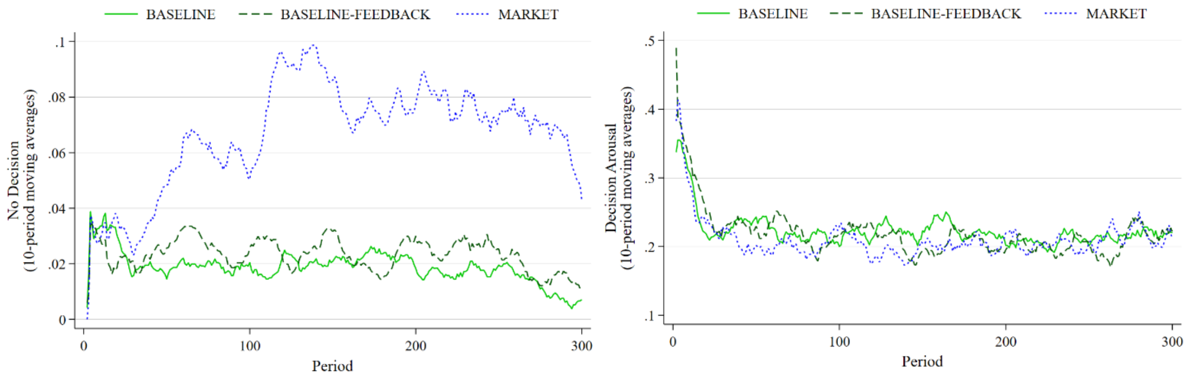


Figure B3. Evolution of no decision dummy (left panel) and decision arousal (right panel) across treatments. Period averages are shown on the graph.

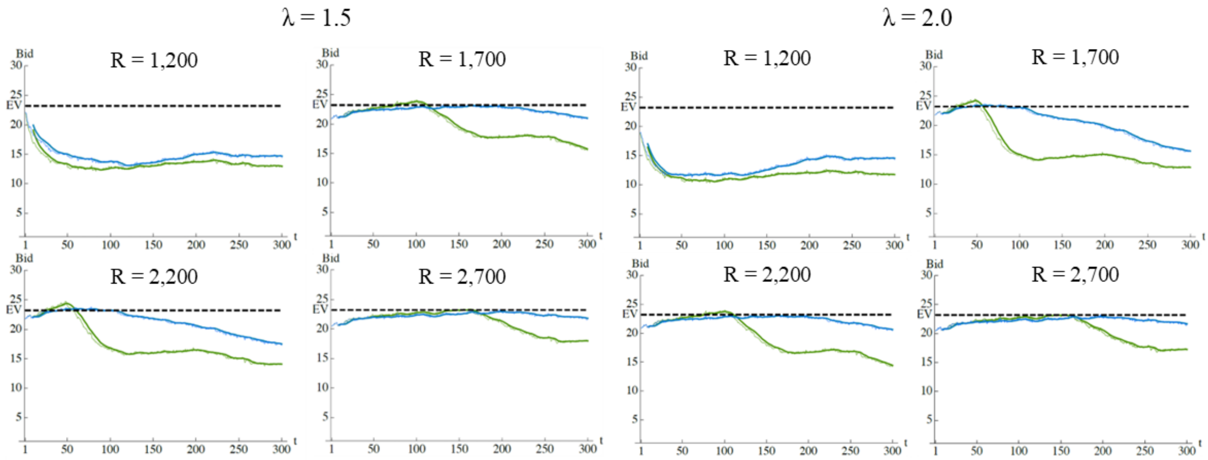


Figure B4. Simulations of bids for eight prospect theory specification including four reference points (1,200¢, 1700¢, 2,200¢ and 2700¢) and two loss aversion parameters ($\lambda = 1.5$ on left panel, and $\lambda = 2.0$ on right panel). For each simulation, we generate six agents, each of them having a randomly selected value for risk aversion (out of ten values: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1.0), which is the exponent (α) of the power utility function (see Online Appendix II for more details). We ran 100 simulations for each specification for Market and Baseline.

Table B4. Arousal and winning bids with low vs high payoff interaction effect. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

DEPENDENT VARIABLE	(1)	(2)	(3)	(4)
	Arousal Dummy			
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

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Win is a dummy that takes value one if a participant bought the asset in a given period. † High Payoff is a dummy taking value one when payoffs were above the median payoff of 30, that is 40 or 50. Median payoff of 30 not included in the regression so that directly compare low (10 or 20) and high (40 or 50) payoffs. Negative payoffs periods are excluded from the analysis (99.2% of the data 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.

Table B5. Arousal and winning bids with payoff interaction effect. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

DEPENDENT VARIABLE	(1)	(2)	(3)	(4)
	Arousal Dummy			
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

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Win is a dummy that takes value one if a participant bought the asset in a given period. Negative payoffs periods are excluded from the analysis (99.2% of the data 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.

Table B6. Arousal and winning bids with money gain interaction effect. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE		Arousal Dummy		
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)
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

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Win is a dummy that takes value one if a participant bought the asset in a given period. † Money Gain is a dummy taking value one when investors obtain a monetary gain in a given period. Negative payoffs periods are excluded from the analysis (99.2% of the data 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.

Table B7. Bids and treatment effects for low base rate arousal investors. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

Low base rate arousal investors	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE		Bid		
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)
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

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Physio Dummy is a dummy that takes value one if a participant was assigned to a session in which physiological recording were used. † Baseline Combined is a dummy variable taking value one if a person is 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 value 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) (Online Appendix 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 1,000 replications for the bootstrapped standard errors.

Table B8. Bids and treatment effects for high base rate arousal investors. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

High base rate arousal investors	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE		Bid		
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

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Physio Dummy is a dummy that takes value one if a participant was assigned to a session in which physiological recording were used. † Baseline Combined is a dummy variable taking value one if a person is 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 value 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) (Online Appendix 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 (6.9% of the data). We used 1,000 replications for the bootstrapped standard errors.

B.3. Earnings and bankruptcy rates

Table B9. Final earnings in cents as a function of base rate arousal, treatment dummies and individual controls. OLS 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 standardize variables.

	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE	Earnings (¢)			
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 in a session	-409.3336****	-402.6040****	-190.2332	-192.1182
	(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	3,903.6759****	3,870.2122****	2,988.0134****	3,000.0339****
	(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*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.

Table B10. 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 standardize variables.

	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE	Bankruptcy Dummy			
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)
Number 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
		(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

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Bankruptcy Dummy takes value one if a participant went bankrupt during the experiment. Market (Baseline-Feedback) is a dummy that takes value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.

B4. Alternative mechanisms

Table B11. Bids and treatment effects (period-market interaction). Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)), including the interaction term 'Market × Period'.

	(1)	(2)
DEPENDENT VARIABLE	Bid	
Market	0.6349	0.3266
	(0.9299)	(0.8986)
Market × Period	0.0115**	0.0119**
	(0.0051)	(0.0052)
Baseline-Feedback	0.6550	0.3519
	(1.0443)	(1.0161)
Physio Dummy	0.6562	0.3426
	(0.9461)	(0.9034)
Number of large losses up to *t*-2	0.3503	0.3744
	(0.2932)	(0.2942)
Asset Payoff in *t*-1	0.0118****	0.0114****
	(0.0024)	(0.0024)
Large Loss Dummy in *t*-1	12.7127****	12.5778****
	(2.4680)	(2.4681)
Period	-0.0423****	-0.0425****
	(0.0034)	(0.0034)
Male Dummy (std)		-0.8432***
		(0.3216)
Risk Aversion (std)		-0.7692**
		(0.3423)
Loss Aversion (std)		-0.8026**
		(0.3860)
Constant	24.6201****	24.9802****
	(1.0075)	(0.9798)
Coefficient Tests		
Market = Baseline-Feedback	0.9863	0.9825
Market = Baseline-Combined†	0.6880	0.8420
R^2	0.0414	0.0563
Observations	157,318	156,291
Number of investors	560	556

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. †Baseline Combined is a dummy variable taking value one if a person is 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.

Table B12. Decision Arousal with added period interactions. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses. (std) stands for standardize variables.

DEPENDENT VARIABLE	(1) No Decision Dummy	(2) Arousal Dummy
Market	0.0250*	-0.0233
	(0.0144)	(0.0254)
Market × Period	0.0000	0.0001
	(0.0001)	(0.0001)
Baseline-Feedback	0.0008	0.0041
	(0.0098)	(0.0262)
Baseline-Feedback × Period	-0.0000	-0.0000
	(0.0000)	(0.0001)
Physio Dummy	-0.0038	
	(0.0096)	
Period	0.0001**	-0.0002
	(0.0001)	(0.0002)
Bid	0.0086****	0.0007***
	(0.0007)	(0.0002)
Number of large losses up to *t*-2	-0.0043	0.0028
	(0.0035)	(0.0064)
Win in *t*-1	-0.0021	-0.0041
	(0.0015)	(0.0027)
Asset Payoff in *t*-1	-0.0001*	0.0000
	(0.0000)	(0.0001)
Large Loss Dummy in *t*-1	-0.0528	0.0189
	(0.0365)	(0.1034)
Constant	-0.1339****	0.3580****
	(0.0216)	(0.0329)
R^2	0.1934	0.0039
Observations	157,318	97,022
Number of investors	560	344

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Win is a dummy that takes value 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 value one if a participant faced an asset paying off a large loss in the previous period.

Table B13. Decision Arousal with added period interactions for investors with low and high baserate arousal. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses. (std) stands for standardize variables.

	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE	No Decision Dummy		Arousal Dummy	
Sample	Low baserate arousal	High baserate arousal	Low baserate arousal	High baserate arousal
Market	0.0152	-0.0459	0.0424*	0.0020
	(0.0290)	(0.0347)	(0.0217)	(0.0307)
Market × Period	-0.0001	0.0001	0.0000	0.0002
	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Baseline-Feedback	-0.0046	-0.0108	0.0155	-0.0345**
	(0.0271)	(0.0289)	(0.0234)	(0.0147)
Baseline-Feedback × Period	-0.0000	-0.0000	-0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Period	0.0002	-0.0005**	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Bid	0.0008***	0.0006*	0.0095****	0.0086****
	(0.0003)	(0.0004)	(0.0011)	(0.0014)
Number of large losses up to *t*-2	-0.0070	0.0008	-0.0034	-0.0059
	(0.0061)	(0.0074)	(0.0053)	(0.0061)
Win in *t*-1	-0.0042	-0.0020	0.0007	-0.0079**
	(0.0047)	(0.0042)	(0.0027)	(0.0033)
Asset Payoff in *t*-1	-0.0002	-0.0000	-0.0002**	-0.0000
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Large Loss Dummy in *t*-1	-0.2084	0.0158	-0.1809**	-0.0375
	(0.1527)	(0.1597)	(0.0864)	(0.0693)
Constant	0.2178****	0.4853****	-0.1539****	-0.1195****
	(0.0470)	(0.0478)	(0.0384)	(0.0354)
R^2	0.0087	0.0086	0.2168	0.1975
Observations	33,905	42,047	33,905	42,047
Number of investors	119	152	119	152

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Win is a dummy that takes value 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 value one if a participant faced an asset paying off a large loss in the previous period.

Table B14. Bids and treatment effects with added interactions. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE		Bid		
Market	2.2791**	2.0235**	2.2587***	1.9927***
	(1.0289)	(0.9754)	(0.7610)	(0.7546)
Market × Large Loss Dummy in *t*-1	0.7206 (0.7944)	0.7667 (0.7950)	-0.0771 (0.4413)	0.0358 (0.4423)
Baseline-Feedback	0.6348	0.3426	0.7008	0.4016
	(1.0463)	(1.0176)	(0.7367)	(0.7300)
Baseline-Feedback × Large Loss Dummy in *t*-1	0.6687 (0.8318)	0.6801 (0.8327)	0.7224* (0.4230)	0.7262* (0.4230)
Physio Dummy	0.6429	0.3248	0.8248	0.5203
	(0.9497)	(0.9074)	(0.6409)	(0.6402)
Number of large losses up to *t*-2	0.3541	0.3741	-1.1493****	-1.1359****
	(0.2908)	(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	12.3185****	12.1639****	14.1179****	13.9372****
	(2.4839)	(2.4819)	(1.1707)	(1.1727)
Period	-0.0391****	-0.0392****		
	(0.0034)	(0.0034)		
Male Dummy (std)		-0.8489***		-0.8859***
		(0.3223)		(0.3069)
Risk Aversion (std)		-0.7811**		-0.7606**
		(0.3421)		(0.3140)
Loss Aversion (std)		-0.7991**		-0.7990**
		(0.3855)		(0.3153)
Constant	24.1881****	24.5328****	24.1644****	24.4926****
	(1.0040)	(0.9764)	(0.6543)	(0.6522)
Coefficient Tests				
Market × Large Loss Dummy in *t*-1= Baseline-Feedback × Large Loss Dummy in *t*-1	0.9518	0.9197	0.0908	0.1449
R^2	0.0389	0.0538	0.0312	0.0459
Observations	157,318	156,291	157,318	156,291
Number of investors	560	556	560	556

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. †Baseline Combined is a dummy variable taking value one if a person is 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin 2013, Block 4}.

Table B15. Bids, treatment effects and rare losses. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE		Bid		
Market	1.9784*	1.6842	2.4380***	2.1418**
	(1.1263)	(1.0624)	(0.8627)	(0.8564)
Market × Zero-to-One Rare Losses Dummy	0.9490	1.0574	-0.5568	-0.4552
	(1.8624)	(1.8024)	(1.2599)	(1.2404)
Baseline-Feedback	0.6399	0.3466	0.7063	0.4077
	(1.0462)	(1.0174)	(0.7363)	(0.7297)
Physio Dummy	0.6436	0.3242	0.8246	0.5208
	(0.9504)	(0.9070)	(0.6405)	(0.6400)
Number of large losses up to *t*-2	0.3551	0.3752	-1.1499****	-1.1364****
	(0.2904)	(0.2920)	(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	12.7166****	12.5769****	14.3139****	14.1655****
	(2.4409)	(2.4398)	(1.1522)	(1.1543)
Period	-0.0391****	-0.0392****		
	(0.0034)	(0.0034)		
Male Dummy (std)		-0.8486***		-0.8861***
		(0.3232)		(0.3068)
Risk Aversion (std)		-0.7796**		-0.7612**
		(0.3424)		(0.3139)
Loss Aversion (std)		-0.8068**		-0.7958**
		(0.3829)		(0.3153)
Constant	24.1848****	24.5310****	24.1636****	24.4907****
	(1.0062)	(0.9777)	(0.6540)	(0.6519)
R^2	0.0394	0.0545	0.0315	0.0460
Observations	157,318	156,291	157,318	156,291
Number of investors	560	556	560	556

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Zero-to-One Rare Losses Dummy takes value one if the total number of rare losses in a session is either zero or one. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. †Baseline Combined is a dummy variable taking value one if a person is 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin 2013, Block 4}.

Table B16. Arousal and winning bids with added interactions. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

DEPENDENT VARIABLE	(1)	(2)	(3)	(4)
	Arousal Dummy			
Market × Win	0.0454****	0.0451****	0.0458****	0.0454****
	(0.0099)	(0.0100)	(0.0068)	(0.0068)
Market	-0.0000	-0.0008	-0.0001	-0.0011
	(0.0193)	(0.0179)	(0.0188)	(0.0187)
Market	0.0402	0.0401	0.0379	0.0376
× Large Loss Dummy in *t*-1	(0.0338)	(0.0342)	(0.0376)	(0.0379)
Baseline-Feedback × Win	0.0108	0.0105	0.0095	0.0091
	(0.0085)	(0.0086)	(0.0063)	(0.0063)
Baseline-Feedback	0.0031	-0.0003	0.0043	0.0008
	(0.0194)	(0.0190)	(0.0179)	(0.0179)
Baseline-Feedback	-0.0165	-0.0143	-0.0171	-0.0149
× Large Loss Dummy in *t*-1	(0.0338)	(0.0340)	(0.0344)	(0.0345)
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	0.0665	0.0545	0.0268	0.0166
	(0.1042)	(0.1052)	(0.0965)	(0.0970)
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	0.3109****	0.3108****	0.1638****	0.1643****
	(0.0254)	(0.0254)	(0.0122)	(0.0122)
Coefficient Tests				
Market × Large Loss Dummy in *t*-1= Baseline-Feedback × Large Loss Dummy in *t*-1	0.0951	0.1155	0.1800	0.2040
R^2	0.0083	0.0112	0.0026	0.0055
Observations	96,264	95,243	96,264	95,243
Number of investors	344	340	344	340

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Win is a dummy that takes value one if a participant bought the asset in a given period. Negative payoffs periods are excluded from the analysis (99.2% of the data 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.

Table B17. Bids, treatment effects and high risk aversion. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE		Bid		
Market	2.3621**	1.9045*	2.3310***	1.8661**
	(1.0205)	(0.9942)	(0.7888)	(0.7889)
Market ×	-0.6961	1.0569	-0.6564	1.0797
High Risk Aversion Dummy	(1.9779)	(2.0764)	(1.8741)	(1.9635)
Baseline-Feedback	0.6397	0.3384	0.7063	0.3978
	(1.0461)	(1.0167)	(0.7365)	(0.7300)
Physio Dummy	0.6426	0.3055	0.8246	0.5008
	(0.9479)	(0.9129)	(0.6407)	(0.6411)
Number of large losses up to t-2	0.3542	0.3742	-1.1493****	-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	12.7161****	12.5759****	14.3144****	14.1658****
	(2.4410)	(2.4399)	(1.1522)	(1.1543)
Period	-0.0391****	-0.0392****		
	(0.0034)	(0.0034)		
Male Dummy (std)		-0.8560***		-0.8933***
		(0.3224)		(0.3071)
Risk Aversion (std)		-0.8429**		-0.8235**
		(0.3544)		(0.3341)
Loss Aversion (std)		-0.7815**		-0.7812**
		(0.3888)		(0.3169)
Constant	24.1854****	24.5462****	24.1631****	24.5074****
	(1.0028)	(0.9764)	(0.6542)	(0.6527)
R^2	0.0390	0.0540	0.0314	0.0462
Observations	157,318	156,291	157,318	156,291
Number of investors	560	556	560	556

**** p-value < 0.001, *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1. High Risk Aversion Dummy takes value one if the total number of safe choices in the Holt and Laury (2002) elicitation task is equal to eight or more. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. †Baseline Combined is a dummy variable taking value one if a person is 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin 2013, Block 4}.

Table B18. Bids, treatment effects and high risk aversion rank. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE		Bid		
Market	2.4087**	2.0191**	2.3939***	1.9971**
	(0.9597)	(0.9049)	(0.7863)	(0.7842)
Market ×	-1.1889	0.0937	-1.3010	-0.0381
Rank Risk	(2.2273)	(2.3615)	(1.9203)	(1.9870)
Baseline-Feedback	0.6391	0.3472	0.7056	0.4074
	(1.0461)	(1.0174)	(0.7361)	(0.7301)
Physio Dummy	0.6382	0.3239	0.8198	0.5208
	(0.9502)	(0.9067)	(0.6404)	(0.6405)
Number of large losses up to *t*-2	0.3541	0.3742	-1.1493****	-1.1358****
	(0.2907)	(0.2922)	(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	12.7160****	12.5761****	14.3144****	14.1659****
	(2.4410)	(2.4399)	(1.1522)	(1.1543)
Period	-0.0391****	-0.0392****		
	(0.0034)	(0.0034)		
Male Dummy (std)		-0.8499***		-0.8856***
		(0.3270)		(0.3077)
Risk Aversion (std)		-0.7856**		-0.7588**
		(0.3505)		(0.3281)
Loss Aversion (std)		-0.7971**		-0.7999**
		(0.3843)		(0.3185)
Constant	24.1885****	24.5306****	24.1666****	24.4905****
	(1.0038)	(0.9772)	(0.6539)	(0.6524)
R^2	0.0393	0.0538	0.0319	0.0459
Observations	157,318	156,291	157,318	156,291
Number of investors	560	556	560	556

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Rank Risk is a dummy that takes value one if a person is the most risk-averse in their experimental group. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. †Baseline Combined is a dummy variable taking value one if a person is 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin 2013, Block 4}.

Table B19. Arousal, winning bids and high risk aversion. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

DEPENDENT VARIABLE	(1)	(2)	(3)	(4)
	Arousal Dummy			
Market × Win × High Risk Aversion	-0.0035	-0.0045	-0.0009	-0.0018
	(0.0267)	(0.0265)	(0.0199)	(0.0199)
Market × Win	0.0456****	0.0454****	0.0458****	0.0455****
	(0.0105)	(0.0107)	(0.0070)	(0.0071)
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	0.0708	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)
R^2	0.0083	0.0112	0.0026	0.0055
Observations	96,264	95,243	96,264	95,243
Number of investors	344	340	344	340

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. High Risk Aversion Dummy takes value one if the total number of safe choices in the Holt and Laury (2002) elicitation task is equal to eight or more. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Win is a dummy that takes value one if a participant bought the asset in a given period. Negative payoffs periods are excluded from the analysis (99.2% of the data 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.

Table B20. Arousal, winning bids and high risk aversion rank. Linear panel regressions with random effects and period fixed effects along with robust standard errors clustered at the session level in parentheses ((1) and (2)). In (3) and (4), AR(1) autoregressive errors are used, and no period variable and period fixed effects are included. (std) stands for standardize variables.

DEPENDENT VARIABLE	(1)	(2)	(3)	(4)
	Arousal Dummy			
Market × Win × Rank Risk	0.0311	0.0299	0.0370*	0.0357*
	(0.0263)	(0.0263)	(0.0197)	(0.0197)
Market × Win	0.0426****	0.0424****	0.0425****	0.0422****
	(0.0101)	(0.0102)	(0.0070)	(0.0071)
Market	0.0005	-0.0004	0.0004	-0.0006
	(0.0193)	(0.0178)	(0.0188)	(0.0187)
Baseline-Feedback × Win	0.0108	0.0105	0.0096	0.0092
	(0.0085)	(0.0086)	(0.0063)	(0.0063)
Baseline-Feedback	0.0030	-0.0005	0.0041	0.0006
	(0.0194)	(0.0190)	(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	0.0714	0.0599	0.0313	0.0214
	(0.1010)	(0.1020)	(0.0953)	(0.0958)
Period	-0.0003**	-0.0003**		
	(0.0001)	(0.0001)		
Male Dummy (std)		0.0247***		0.0248***
		(0.0077)		(0.0075)
Risk Aversion (std)		0.0075		0.0081
		(0.0061)		(0.0073)
Loss Aversion (std)		0.0018		0.0016
		(0.0090)		(0.0074)
Constant	0.3108****	0.3107****	0.1638****	0.1643****
	(0.0254)	(0.0254)	(0.0122)	(0.0121)
R^2	0.0085	0.0113	0.0027	0.0056
Observations	96,264	95,243	96,264	95,243
Number of investors	344	340	344	340

**** *p*-value < 0.001, *** *p*-value < 0.01, ** *p*-value < 0.05, * *p*-value < 0.1. Rank Risk is a dummy that takes value one if a person is the most risk-averse in their experimental group. Market (Baseline-Feedback) is a dummy that takes value one if a participant was assigned to the Market (Baseline-Feedback) treatment. Win is a dummy that takes value one if a participant bought the asset in a given period. Negative payoffs periods are excluded from the analysis (99.2% of the data 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 value 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) (Online Appendix I, Block 1) {Brink and Rankin, 2013, Block 4}.