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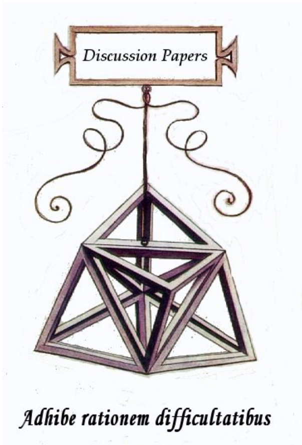

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Emotions in hybrid financial markets

Discussion paper n. 311

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Discussion paper

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Emotions in hybrid financial markets

Abstract

We investigate whether human traders experience milder emotions when participating in a financial market populated by artificial agents as opposed to a market comprising solely humans. In particular, by manipulating across conditions the number of artificial players, we assess how much emotions vary along with price dynamics (i.e. the occurrence of price bubbles). Notably, to ensure robustness, we evaluate emotions using three distinct methods: self-reporting, physiological responses, and facial expressions. Results show larger bubbles and milder emotional reactions in conditions with a higher count of artificial agents. Furthermore, negative emotions indirectly contribute to the mitigation of price bubbles. Ultimately, we observe a moderate degree of consistency across emotional measurements, with self-reported data being the least consistent among them.

Keywords: Emotions, Financial Bubbles, Artificial Players

JEL CLassification: G10; G41

Emotions in hybrid financial markets

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Abstract

We investigate whether human traders experience milder emotions when participating in a financial market populated by artificial agents as opposed to a market comprising solely humans. In particular, by manipulating across conditions the number of artificial players, we assess how much emotions vary along with price dynamics (i.e. the occurrence of price bubbles). Notably, to ensure robustness, we evaluate emotions using three distinct methods: self-reporting, physiological responses, and facial expressions. Results show larger bubbles and milder emotional reactions in conditions with a higher count of artificial agents. Furthermore, negative emotions indirectly contribute to the mitigation of price bubbles. Ultimately, we observe a moderate degree of consistency across emotional measurements, with self-reported data being the least consistent among them.

1 Introduction

Real financial markets are nowadays largely populated by algorithms. Artificial players are estimated to be responsible for at least 70% of market transactions. For example, market-makers, a very specific type of artificial traders, are said to be part of 70% of the electronic trades in the United States, 40% in the European Union (EU), and 35% in Japan. Some of these artificial traders are "official", i.e., there is an agreement with an exchange to maintain fair and orderly markets (e.g. Designated Market Makers, [1]) while others are not (e.g. high-frequency traders, [2]). As a result, the presence of artificial traders may imply both benefits and harms for market efficiency and stability (e.g. the Flash Crash in 2010, [3]).

Since the seminal work of Smith, Suchanek, and Williams [4] (SSW in the following), experimental research has significantly contributed to understanding the dynamics of price bubbles. In particular, a strand of literature has focused on how trading algorithms affect human traders' behavior and market performance (see[5] for a review). Studies have shown that markets composed entirely of humans or algorithms exhibit lower price convergence compared to hybrid markets. Additionally, some research indicates that no bubbles form when artificial

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traders buy and sell at fundamental values, highlighting the influence of algorithm design on market outcomes[5].

However, recent literature suggests that artificial players can influence market price dynamics by affecting human expectations. For example, some studies find that the mere expectation of interacting with artificial agents may reduce financial bubbles [6]. Others observe that informing participants about artificial traders' involvement also reduces bubbles compared to when participants are unaware [7]. Conversely, there is evidence that the potential presence of algorithmic traders can lead to greater deviations from market fundamentals and alter trading behavior over time[8].

We aim to contribute to the literature on the impact of artificial players on human behavior and expectations by examining the emotional state of market participants. Our study assesses the consistency across three distinct types of emotion measurement: physiological parameters (such as electrodermal activity and heart-rate variability), facial expressions, and self-reported measures. Previous studies have primarily relied on single measures, and only occasionally on two ([9], [10]). Many studies have solely considered mood proxies, such as investor sentiment ([11]).

Research indicates that market bubbles increase in magnitude and amplitude if participants are aroused or excited. For example, inducing emotions like excitement can result in larger bubbles compared to calmer states or fear[12]. Positive emotional states are linked to increased purchases and overpricing, while fear leads to selling and price decreases[10]. Experienced traders are less influenced by emotions, suggesting that irrational traders are more affected[13]. Additionally, rising prices are associated with increased fear and hope, whereas falling prices increase fear and decrease hope[11]. Strong emotional responses to negative tail events can have contrasting effects based on the specific emotion, with loss-averse investors showing increased bids when emotionally aroused[14].

While most investigations rely on a single measure of emotions, some exceptions compare at most two measurement types. For example, some studies use both self-reported measures and facial expression analysis software to monitor participants' emotional states[9, 10]. These studies primarily aim to evaluate the influence of positive emotional states on behavior, focusing on six fundamental emotions (happiness, sadness, fear, disgust, anger, surprise). Discrepancies between the measures of emotions have been observed, though the reasons remain unclear[9].

The current research has two main objectives. First, we intend to evaluate whether human participants in hybrid financial markets, where artificial players make up a significant proportion, display milder emotional responses. Additionally, our goal is to assess emotions through three distinct methods (self-reported, physiological parameters, and facial readings) and ascertain the level of agreement among these measures and their direct and indirect impact on price bubbles.

To achieve the first aim, we employ the multi-asset market set-up detailed in [15], which extends the SSW set-up to include artificial players. In particular, this set-up involves a mix of human traders and artificial agents trading two fictous stocks while keeping costant the overall market size, that is the number of total players in the market. While we keep the role of artificial players consistent across different conditions, we vary their numbers. In particular, participants are randomly assigned to three conditions: *AI-Majority*, where the market consists of a ratio of 1 human to 7 artificial players; *AI-Equal*, which maintains a balanced ratio of 4 human to 4 artificial players; and *Humans*, where the market exclusively comprises 8 human traders without artificial players.

To achieve the second aim, we rely on three distinct techniques. First, we gather self-reported measures by periodically asking participants to rate their emotions, encompassing feelings of sadness, disgust, surprise, happiness, anxiety, fear, and boredom. Secondly, emotions are assessed through physiological parameters, such as heart rate and skin conductance ([16]). These measures are indicators of autonomic nervous system (ANS) which is responsible of emotion regulation, and provides information about physiological arousal and valence dyamics. Lastly, we leverage a facial expression analysis software developed by Emotiva Srl, an artificial intelligence company specializing in emotion recognition.[1] This technology employs computer vision and machine learning algorithms to analyze real-time emotional responses. This method captures the same emotions as in self-reported measures like anger, disgust, fear, happiness, sadness, and surprise, while also gauging attention and engagement levels.

Our analyses thus test four hypotheses. Drawing from earlier research (as exemplified by [17]), we anticipate that emotions are less intense in markets with a higher proportion of artificial traders. Specifically, we hypothesize that the emotional state of human participants surpass that of human participants in the *AI-Equal* condition, which in turn surpass those in the *AI-Majority* condition (Hypothesis 1). Moreover, we also expect larger deviation of prices from fundamental values in treatment with a larger number of artificial noise players, the effect being stronger for the speculative asset (Hypothesis 2). Building on insights from previous investigations (for instance, [11]), we also predict negative emotional responses to reduce the price bubbles. In other words, we expect a larger direct effect of emotion on price bubbles and to observe an indirect weaker mediating role of emotions in fostering the price bubble when playing in market largely populated with artificial players (Hypotheses 3). Finally, we anticipate encountering moderate consistencies across the three measurement categories of emotion; however, as in previous research (for example, [9]), we do expect the self-reported measures to demonstrate reduced informativeness (Hypothesis 4).

2 Methods

2.1 Ethics information

Our research complies with all relevant ethical regulations. The study was approved by the Committee on Bioethics of the University of Pisa (Review No. 29/2023). Informed consent was obtained from all participants of the study.

2.2 Design

We rely on the multi-asset market set-up as described in [15], which is an extension to the two asset case of the market in SSW, and features the presence of artificial agents along with human traders. At this link https://crossedmarket.herokuapp.com/demo/ it is possible to visit our platform and simulate an experimental session. The SSW set-up has been widely used in experimental finance ([18, 19]) The experimental market features two types of artificial players: noise traders, which emulate the behavior of inexperienced human traders in SSW experiments ([20],[21]), and market-makers, which provide liquidity posting quotes within the bid-ask spread according to the model of [22]. The role of artificial players remain identical over treatments (i.e. they are programmed in the same way), although across conditions we vary the number of noise traders, while keeping constant to 2 the number of market-makers. In particular, our design is between-subject, participants are randomly assigned to one (and only one) of three conditions:

1. **AI-majority:** participants are informed that in the market there there are both human and artificial players in a ratio of 1 to 7;

2. **AI-Equal:** participants are informed that the market include both human and artificial players in a balanced ratio of 4 to 4;

[1]For more details, visit: http://emotiva.it/en/emotion-ai-company/

3. **Humans:** participants are informed that the market exclusively comprises human traders, specifically 8 humans with no artificial players.

The market is modelled as a continuous double-auctions open limit order book (see e.g. [23, 24, 4]). The traders can either select offers already in the book or may enter their own ones by using a specific button. It is not possible to identify the identity of the submitter (be they a human or an artificial). As in [25], participants have a unique portfolio for trading two assets: one value asset (with a constant fundamental value) and a speculative asset (with a decreasing fundamental value).

The experiment is expected to span approximately one hour. During this time, each playing period last for 180 seconds, with a total of 15 periods. To start, there is an initial rest phase lasting around 3 minutes. During this phase, physiological and facial parameters are collected to assess the emotional state of each participant at the outset of the experiment (that serve as a baseline). Additionally, participants are given a questionnaire to gauge self-reported emotional indicators at the conclusion of periods 5, 10, and 15. The experiment conclude with an exit questionnaire designed to gather further characteristics from the participants.

2.3 Measurement of financial bubbles

In line with literature, e.g. [24], we derive a measure of price bubbles using the relative absolute deviation (RAD) of each stock price from its expected fundamental value:

$$RAD = \left(\frac{1}{N}\right) \sum_{r=1}^{N} \left| \frac{\bar{P}_r - FV_r}{FV_r} \right|$$

where $\bar{P}_r$ is the average price in round r, with $r = 1, ..., 15$ and FV is the fundamental value in that round. For example, a RAD of 0.1 indicates that prices differ on average by 10% from the fundamental value.

2.4 Measurement of emotions

We measure emotions in three different ways:

1. **Self-reported measures:** we ask participants every five rounds how they feel. In particular, we ask participants at the end of round 5,10, and 15 on likert scale from 1 to 7 how much they are: anger, sad, disgusted, surprised, happy, anxious, scared, bored. These are the same emotions generated with the face-reading software. We limit the request to answer these questions only to three periods to avoid bothering the subjects while playing.

2. **Physiological parameters:** we derive emotions' indicators by monitoring the psycho-physiological states of our participants through a wearable device. We collect data on autonomic nervous system correlates (ANS), such as pulse rate variability (PRV) and electrodermal activity (EDA), which are well known to contain information about the affective state of a subject ([16]). Both EDA and PPG signals are acquired using a Shimmer3 GSR+ unit (Shimmer, USA) at the sampling frequency of 250Hz. We record EDA pacing Ag/AgCl electrodes on the proximal phalanx of the first and second fingers of the subjects' non-dominant hand, respectively, whereas we record PPG at the fingertip of the first finger. For additional information, see supplementary information in 6. To address inter-individual variability, all indicators are considered as relative measure compared to their own value during the starting rest phase, as described in Section 2.2.

3. **Facial expressions:** we also measure derive emotions through a facereading software in collaboration with researchers at the "*Emotiva Srl*" company.[2] In particular we measures the same emotions as in self-reported questionnaire (anger, disgust, fear, happiness, sadness, surprise, boredom) plus a measure of attention and engagement. The face analysis has been conducted processing RGB video frames sampled at 7Hz (7 frames per second). The emotions are estimated combining the activations of 17 facial expressions (or Action Units, following the FACS [26] encoding system). The levels of attention are estimated detecting and processing the subjects' head pose. The engagement is estimated as a linear combination of emotions. To address inter-individual variability, we computed and subtracted a subject-specific baseline averaging the emotional values observed during the starting rest phase, as described in Section 2.2. Instead, the individual baseline for attention has been computed averaging the subject's head pose in a 10 seconds running window, to balance the possible pose adjustments that the subjects could have given the length of the experiment.

3 Data Acquisition

3.1 Data Collection

Between April and July 2023, we collected financial market data across three conditions: 9 sessions for *AI-Equal* with a total of 36 participants, 3 sessions for *Humans* with a total of 24 participants, and 12 sessions for *AI-Majority* with a total of 12 participants. In total, 72 participants took part in the experiment. Each participant provided self-reported measures at rounds 5, 10, and 15, while physiological and face-reading measures were collected in every round. Table 1 summarizes the sample and available data for each measurement type.

3.2 Data Pre-processing

Average Measures: To control for correlations of individual observations in each financial market, we computed the average emotion levels for each group of human players and retained one independent observation per group per period. Due to technical issues, physiological data were obtained from 20 participants in *AI-Equal*, 24 in *Humans*, and 12 in *AI-Majority*. Facial expression data were processed for 35 participants in *AI-Equal*, 21 in *Humans*, and 12 in *AI-Majority*. Table 1 provides an overview of the number of independent observations.

Outliers: All responses of participants included in the sample were analyzed.

3.3 Hypothesis testing

We examine price and emotional measures in three separate models (means comparisons, mediation analysis and consistencies across measures). For testing our hypotheses, in order to account for multiple assessment, we follow recent suggestions by considering results passing a α of p < 0.005 is interpreted as 'supportive evidence' for our hypotheses, while results passing a corrected α of p< 0.05 as 'suggestive evidence'.

Hypothesis 1: Given the evidence of previous studies in which humans, in general, tend to appear less emotional when interacting with artificial players (see [27] for a review), we hypothesize to observe weaker emotions in market with a larger number of artificial traders: that is $Emotions_{Humans} > Emotions_{AI-Equal} > Emotions_{AI-Majority}$.

[2] Emotiva is a deep tech artificial intelligence company sharpened on emotion recognition. It develops computer vision and machine learning algorithms to analyze people's emotional responses in real-time. See http://emotiva.it/en/emotion-ai-company/

Hypothesis 2: The evidence of previous experimental papers also suggest that financial bubbles are reduced when humans interact with artificial players traders, especially if they trade at the fundamental values ([17]). In our case, however, artificial players tend to behave as inexperienced traders in financial market and can be considered "near-zero-intelligence" agents (see [20], [21] and [25]). Therefore, whenever their number increases in the market, we expect to observe larger bubbles, that is $RAD_{Humans} < RAD_{AI-Equal} < RAD_{AI-Majority}$. Moreover, we expect all this effect to be stronger for the speculative assets (i.e. asset A).

To test these two hypotheses, we compare the average measures of emotions (for each of the three types of measurement) and our measure of mispricing (relative absolute deviations, RAD) across conditions. Specifically, for emotions, we consider a broad range of measures but expect strong evidence for those that appeared relevant in previous studies, such as the sympathetic branch (i.e., the EDAsymp index).

Hypothesis 3: We expect positive emotions (such as happiness) to play a direct positive role in fostering price bubbles, while we expect negative emotions (such as anger and fear) to reduce bubbles. Although it is not possible to directly associate valence and arosual to any specific type of emotions, we also expect that higher valence to be associated to larger bubbles. On top of that, we also expect emotions to play an indirect effect that goes through the interaction with different type of players. In particular we expect this effect to be weaker when playing in market largely populated with artificial players.

Hypothesis 4: To check consistency across measures, in addition to control whether different measures lead to analogous results when testing hypothesis 1, 2, and 3, we follow [10] and compute a measure of valence for both self-reported and facial expression indicators as $valence = happiness - 0.25(anger + fear + sadness + disgust)$. This measure can be considered as a net positivity measure of an emotional state and its consistencies is evaluated with arosual measures derived from physiological paramater acquisition.

In particular, we check whether it exits a U-relationship by running the following regression:

$$Physio\,Indicator_{st} = \alpha + \beta_1 valence_{st} + \beta_2 valence_{st}^2 + u_{1st} \quad (1)$$

where $Physio\,Indicators$ is the average level per session s in round t of one of our indicators of arousal, and valence is the synthetic measure derived from self-reported and facial expression measures. In particular, we consider only those physiological indicators that have a clear connection with a state of arousal such as *Meantonic, Ampsum, Edasymp.*

In addition, we follow [28] and test for the presence of an U-relationship based on the following joint null hypotheses:

H_0: $\beta_1 + 2\beta_2 valence_{min} \geq 0 \bigcup \beta_1 + 2\beta_2 valence_{max} \leq 0$ against the alternative

H_1: $\beta_1 + 2\beta_2 valence_{min} < 0 \bigcap \beta_1 + 2\beta_2 valence_{max} > 0$

where $valence_{min}$ and $valence_{max}$ are the minimum and maximum values of the valence indicator respectively.

4 Experimental results

All data and codes are available at this link. `https://github.com/caterinagiannetti/Emotions-in-hybrid-markets`.

4.0.1 Testing hypothesis 1: Emotions in financial markets

We begin by testing hypothesis 1, that is we check whether emotions are stronger in market populated by humans players. Table (2) compares self-reported measures across conditions. No significant results emerge, possibly due to the low power we have for this measure. Table (3 compares across conditions the level of emotions as retrieved from the reading of facial

Table 1: SAMPLE SIZE ACROSS TREATMENTS

	Individuals	Humans per group	Independent obs	Independent obs x rounds	Self-reported (3 obs x session)	Face reading (15 obs x session)	Physio (15 obs x session)
AI-Equal	36	4	9	135	27	131	75
Humans	24	8	3	45	9	40	145
AI-Majority	12	1	12	189	36	180	180
	72			369	72	351	300

expressions. Indeed, people seem to experience less anger when playing in markets populated by humans ($Anger_{Humans} - Anger_{AI-Majority} = -0.0310$ significant at 0.1% level, effect size $d = -0.558$), but are at the same time more sad ($Sad_{Humans} - Sad_{AI-Majority} = 0.0267$ significant at 5% level, effect size $d = 0.406$) and bored ($Bored_{Humans} - Bored_{AI-Majority} = 0.0286$ significant at 1% level, effect size $d = 0.536$). In addition, they also appear to be less engaged ($Engagement_{Humans} - Engagement_{AI-Majority} = -0.0208$ significant at 1% level, effect size$d = -0.489$) and less attentive when playing against humans ($Attention_{Humans} - Attention_{AI-Majority} = -0.0263$ significant at 0.1% level, $d = -0.642$).

In Table (4) we contrast different physiological measures. In particular, emotions regulation process modulates the sympathovagal balance, which is considered a reliable marker of the human affective state. In line with previous studies, we employed indexes of the sympathovagal dynamics based on the combination of the information extracted from the EDA and Pulse Rate Variability signal. Indeed, among the many measures collected, lf/hf and $EDAsymp\_hf$ turned out as expected to be the most informative: indeed, across conditions, we observe that there is a positive difference whenever the market comprises a larger number of humans. In fact, $EDASymp\_HF_{Equal} - EDASymp\_HF_{AI-Majority} = 27622.6$ significant at 1% level, effect size $d = 0.446$) $EDASymp\_HF_{Humans} - EDASymp\_HF_{AI-Majority} = 25541.6$ significant at 5% level, effect size $d = 0.387$). However, we also observe significant variation across conditions of $Ampsum$ and $Meantonic$ which respectively represent the state of activation and reaction to discrete events of a subject. In this case, $meantonic_{Equal} - meantonic_{Humans} = 0.272$ significant at1% level, effect size $d = 0.547$, while $Ampsum_{Equal} - Ampsum_{Humans} = -4.366$ significant at 5% level, effect size $d = 0.786$. This evidence overall suggests that the base activation is larger when humans are interacting with artificial players but express stronger reaction during the market phases with humans. Overall the evidence from physiological measures is thus consistent with the measurement of facial reading: participants tend to be engaged and attentive when playing against artificial players. However, they emotional reaction is stronger when playing against humans.

4.0.2 Testing Hypothesis 2: Bubbles in financial markets

We now test Hypothesis 2. As expected, financial bubbles are larger in market largely populated by artificial (noise) players. In table (5) we indeed observe that the relative absolute deviation of stock A from its fundamental value is significantly lower in markets populated solely by humans rather than by artificial players. Indeed, $RAD_{AI-Equal} - RAD_{Humans} = 0.954$ significant at 0.1% level means that, when market comprises artificial players along with humans, prices deviates from the fundamental value about 95% more than when market comprises human players only. Moreover, $RAD_{AI-Equal} - RAD_{AI-Majority} = -0.642$ meaning that by further increasing the number of artificial players bubbles get larger. Results for stock B are qualitatively similar.

Table 2: Self-reported measures: comparisons across treatments

	means comparisons			Effect size - Cohen's d		
	Equal vs AI-Majority	**Humans vs AI-Majority**	**Equal vs Humans**	**Equal vs AI-Majority**	**Humans vs AI-Majority**	**Equal vs Humans**
	(1)	(2)	(3)	(4)	(5)	(6)
Happiness	-0.287	-0.0556	-0.231	-.25	-.044	-.308
	(-0.98)	(-0.12)	(-0.80)	[-.75 , .252]	[-.775 , .686]	[-1.064 , .452]
Sadness	0.306	0.458	-0.153	.295	.422	-.189
	(1.16)	(1.13)	(-0.49)	[-.208 , .796]	[-.317 , 1.155]	[-.943, .568]
Surprise	-0.657*	-0.250	-0.407	-.54	-.18	-.576
	(-2.12)	(-0.48)	(-1.50)	[-1.046 , -.03]	[-.91 , .553]	[-1.338 , .195]
Disgusted	0.0926	-0.319	0.412	.074	-.24	.494
	(0.29)	(-0.64)	(1.28)	[-.425 , .573]	[-.971 , .493]	[-.273 , 1.254]
Anxiety	-0.444	-0.153	-0.292	-.284	-.083	-.459
	(-1.12)	(-0.22)	(-1.19)	[-.785 , .219]	[-.813 , .648]	[-1.218 , .306]
Fear	-0.491	-0.389	-0.102	-.325	-.225	-.142
	(-1.28)	(-0.60)	(-0.37)	[-.826 , .178]	[-.956 , .508]	[-.896 , .614]
Boredom	0.120	0.444	-0.324	.102	.362	-.302
	(0.40)	(0.97)	(-0.78)	[-.398 , .601]	[-.375 , 1.094]	[-1.057 , .458]
Valence2	-0.256	0.0278	-0.284	-.189	.021	-.238
	(-0.74)	(0.06)	(-0.62)	[-.688 , .312]	[-.71 , .751]	[-.993 , .52]
N	63	45	36	63	45	36

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.0.3 Testing Hypothesis 3: Mediation analysis

In this section, we test the direct and indirect effects that emotions have on bubbles by conducting a series of mediations analysis, relying on those indicators that appear more relevant in the analysis conducted above.

In Table (6) we observe that the direct effect of higher LF_HF is negative and statistically significant (-0.135 significant at 0.1% level). That is, whenever there is an an alteration of the sympatho-vagal balance, i.e. whenever subjects are not "calm", there is a reduction in the price bubble dynamics for the speculative asset (A). Moreover, this effect is reinforced when players interact in the market with other humans, i.e. there is an additional negative indirect effect that further reduces the bubbles in Equal and Humans (-0.088 and -0.111 significant at 1%level). These effects are similar but milder for the value asset (B). However, only observing LF_HF can lead to ambiguities.

Eda Symp is a simple measure of sympathetic activity only. In that case, we observe in Table (7), there is a direct effect of Eda Symp on price bubbles, that a higher Eda Symp implies a positive and statistically significant increase in the price bubble dynamics for the speculative asset (A) (0.034 significant at 0.1% level). However, the indirect effects are positive but not statistically significant. Table (8) and Table (9) report the results for Meantonic and Ampsum respectively: even in this case, the direct effects appear positive and statistically significant, while the indirect effects are positive and marginally signficant. No significant results emerge for the value asset (B).

Table 3: FACE EXPRESSION MEASURES: COMPARISONS ACROSS TREATMENTS

	MEAN COMPARISONS			EFFECT SIZE - COHEN'D		
	Equal vs AI-Majority	**Humans vs AI-Majority**	**Equal vs Humans**	**Equal vs AI-Majority**	**Humans vs AI-Majority**	**Equal vs Humans**
	(1)	(2)	(3)	(4)	(5)	(6)
Fear	-0.00567	-0.0154	0.00978	-.105	-.27	.285
	(-0.92)	(-1.62)	(1.66)	[-.328 , .119]	[-.597 , .058]	[-.054 , .623]
Anger	-0.0346***	-0.0310***	-0.00362	-.618	-.558	-.087
	(-5.43)	(-3.35)	(-0.51)	[-.846 , -.39]	[-.889 , -.227]	[-.425 , .25]
Disgust	-0.00499	0.00204	-0.00703**	-.16	.058	-.47
	(-1.40)	(0.35)	(-2.73)	[-.383 , .064]	[-.269 , .384]	[-.810 , -.128]
Happiness	-0.00148	-0.00928	0.00780	-.032	-.184	.276
	(-0.28)	(-1.10)	(1.60)	[-.255 , .191]	[-.511 , .143]	[-.063 , .614]
Sadness	0.0106	0.0267*	-0.0161***	.183	.406	-.656
	(1.61)	(2.44)	(-3.81)	[-.041 , .406]	[.077 , .734]	[-.999 , -.311]
Surprise	-0.00761	-0.0189	0.0113	-.101	-.25	.21
	(-0.89)	(-1.50)	(1.22)	[-.324 , .122]	[-.577 , .078]	[-.128 , .548]
Boredom	-0.00551	0.0286**	-0.0341***	-.11	.536	-1.083
	(-0.96)	(3.22)	(-6.29)	[-.333 , .114]	[.205 , .866]	[-1.438 , -.726]
Attention	0.00865	-0.0263***	0.0350***	.221	-.642	1.39
	(1.94)	(-3.85)	(8.07)	[-.003 , .445]	[-.973 , -.309]	[1.021 , 1.755]
Engagement	0.00527	-0.0208**	0.0260***	.131	-.489	1.005
	(1.15)	(-2.94)	(5.84)	[-.093 , .354]	[-.818 , -.159]	[.65 , 1.357]
Valence	0.00717	-0.00487	0.0120*	.114	-.071	.345
	(1.00)	(-0.42)	(2.00)	[-.11 , .337]	[-.397 , .256]	[.005 , .683]
Valence_check	-0.00147	-0.0137	0.0122*	-.022	-.191	.341
	(-0.20)	(-1.15)	(1.98)	[-.245 , .201]	[-.518 , .136]	[.001 , .679]
N	315	225	180	315	225	180

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, [] confidence intervals

Table 4: PHYSIO MEASURES: COMPARISONS ACROSS TREATMENTS

	MEAN COMPARISONS			EFFECT SIZE - COHEN'D		
	Equal vs AI-Majority	**Humans vs AI-Majority**	**Equal vs Humans**	**Equal vs AI-Majority**	**Humans vs AI-Majority**	**Equal vs Humans**
	(1)	(2)	(3)	(4)	(5)	(6)
maxtonic	0.322*	0.0447	0.278**	.298	.04	.558
	(2.16)	(0.24)	(2.96)	[.027 , .568]	[-.287 , .366]	[.18 , .933]
maxphasic	0.00841	0.0418*	-0.0334***	.071	.339	-.704
	(0.52)	(2.04)	(-3.73)	[-.199 , .34]	[.011 , .667]	[-1.083 , -.323]
meantonic	0.286	0.0143	0.272**	.266	.013	.547
	(1.93)	(0.08)	(2.90)	[-.005 , .536]	[-.314 , .339]	[.17 , .922]
meanphasic	0.00645	0.0287*	-0.0222***	.091	.389	-.78
	(0.66)	(2.33)	(-4.14)	[-.179 , .36]	[.06 , .717]	[-1.162 , -.396]
stdtonic	0.0248***	0.0205*	0.00424	.472	.371	.252
	(3.43)	(2.23)	(1.34)	[.199 , .744]	[.042 , .699]	[-.119 , .623]
stdphasic	-0.000497	0.0110	-0.0115**	-.01	.222	-.538
	(-0.08)	(1.33)	(-2.86)	[-.28 , .259]	[-.105 , .549]	[-.913 , -.161]
ampsum	1.538	5.874*	-4.336***	.11	.406	-.786
	(0.80)	(2.43)	(-4.17)	[-.159 , .38]	[.077 , .734]	[-1.167 , -.401]
smnapeak	0.252	0.843	-0.591**	.09	.292	-.524
	(0.66)	(1.75)	(-2.78)	[-.179 , .36]	[-.036 , .619]	[-.899 , -.148]
meanrr	-0.0217**	-0.0135	-0.00824	-.435	-.273	-.24
	(-3.16)	(-1.64)	(-1.27)	[-.707 , -.162]	[-.6 , .055]	[-.611 , .131]
stdrr	0.00742	0.00626	0.00116	.224	.187	.067
	(1.63)	(1.12)	(0.36)	[-.046 , .494]	[-.14 , .514]	[-.302 , .437]
rmssd	0.00170	-0.00577	0.00748	.047	-.157	.351
	(0.34)	(-0.94)	(1.86)	[-.223 , .316]	[-.483 , .171]	[-.022 , .723]
pnn50	-0.102	-3.774	3.672*	-.007	-.259	.406
	(-0.05)	(-1.55)	(2.15)	[-.276 , .262]	[-.586 , .069]	[.032 , .778]
lf	-0.000258	-0.000247	-0.0000112	-.062	-.058	-.007
	(-0.45)	(-0.35)	(-0.04)	[-.332 , .207]	[-.384 , .269]	[-.377 , .363]
lfnu	0.993	4.044	-3.051	.052	.209	-.304
	(0.38)	(1.25)	(-1.61)	[-.218 , .321]	[-.119 , .536]	[-.675 , .069]
hf	0.000237	-0.0000203	0.000257	.106	-.009	.196
	(0.77)	(-0.05)	(1.04)	[-.164 , .375]	[-.336 , .318]	[-.175 , .566]
hf_nu	-0.785	-3.868	3.083	-.041	-.201	.311
	(-0.30)	(-1.21)	(1.65)	[-.311 , .228]	[-.528 , .126]	[-.061 , .6820]
lf_hf	0.652**	0.805**	-0.154	.441	.522	-.282
	(3.21)	(3.13)	(-1.50)	[.169 , .713]	[.191 , .851]	[-.653 , .09]
sd1	0.00121	-0.00409	0.00530	.046	-.157	.351
	(0.34)	(-0.94)	(1.86)	[-.223 , .316]	[-.483 , .171]	[-.022 , .723]
sd2	0.0105	0.0116	-0.00111	.248	.27	-.054
	(1.80)	(1.62)	(-0.28)	[-.023 , .518]	[-.058 , .598]	[-.423 , .316]
EDAsymp	0.450	1.586	-1.136**	.074	.251	-.523
	(0.54)	(1.50)	(-2.77)	[-.195 , .344]	[-.077 , .578]	[-.897 , -.146]
EDAsymp_HF	27622.6**	25514.6*	2108.0**	.446	.387	.516
	(3.25)	(2.32)	(2.74)	[.174 , .718]	[.058 , .715]	[.14 , .891]
EDAsymp_HFnu	0.107**	0.102*	0.00489	.443	.402	.064
	(3.22)	(2.41)	(0.34)	[.17 , .714]	[.073 , .73]	[-.305 , .434]
N	255	225	120	255	225	120

t statistics in parentheses

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

Table 5: RELATIVE ABSOLUTE DEVIATIONS - MARKET PRICES: COMPARISONS ACROSS TREATMENTS

	Equal vs AI-Majority	**Humans vs AI-Majority**	**Equal vs Humans**
	(1)	(2)	(3)
RAD_A	-0.642***	-1.597***	0.954***
	(-5.91)	(-10.31)	(4.99)
RAD_B	-0.162*	-0.167	0.00510
	(-2.10)	(-1.55)	(0.04)
N	315	224	179

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Mediation analysis: LF_HF_NU

	direct	**indirect**	**total**	**direct**	**indirect**	**total**
		RAD_A			RAD_B	
LF_HF	-0.135***		-0.135***	-0.074***		-0.074***
	(0.04)		(0.04)	(0.02)		(0.02)
Equal	-0.927***	-0.088**	-1.015***	-0.176**	-0.051**	-0.227***
	(0.13)	(0.04)	(0.13)	(0.08)	(0.02)	(0.08)
Humans	-1.486***	-0.111**	-1.597***	-0.105	-0.062**	-0.167*
	(0.16)	(0.05)	(0.16)	(0.10)	(0.03)	(0.10)
Constant	1.817***			0.554***		
	(0.08)			(0.05)		

*p<0.10,** p<0.05, ***p<0.01

Table 7: Mediation analysis: EDA SYMP

	direct	**indirect**	**total**	**direct**	**indirect**	**total**
		RAD A			RAD B	
EDA SYMP	0.034***		0.034***	0.003		0.003
	(0.01)		(0.01)	(0.01)		(0.01)
Equal	-1.029***	0.014	-1.015***	-0.227***	0.001	-0.227***
	(0.13)	(0.03)	(0.13)	(0.08)	(0.00)	(0.08)
Humans	-1.652***	0.055	-1.597***	-0.172*	0.004	-0.167*
	(0.16)	(0.04)	(0.16)	(0.10)	(0.01)	(0.10)
Constant	2.023***			0.630***		
	(0.07)			(0.05)		

*p<0.10,** p<0.05, ***p<0.01

Table 8: Mediation analysis: MEANTONIC

	direct	indirect	total	direct	indirect	total
		RAD_A			RAD_B	
Meantonic	0.165***		0.165***	0.207***		0.207***
	(0.05)		(0.05)	(0.03)		(0.03)
Equal	-1.061***	0.046*	-1.015***	-0.281***	0.055*	-0.227***
	(0.13)	(0.03)	(0.13)	(0.08)	(0.03)	(0.08)
Humans	-1.606***	0.010	-1.597***	-0.168*	0.001	-0.167*
	(0.16)	(0.03)	(0.16)	(0.09)	(0.03)	(0.10)
Constant	1.884***			0.543***		
	(0.07)			(0.04)		
var(rada)	0.829***			0.302***		
	(0.07)			(0.03)		
var(meantonic)	0.978***			0.929***		
	(0.08)			(0.08)		

*p<0.10,** p<0.05, ***p<0.01

Table 9: Mediation analysis: AMPSUM

	direct	indirect	total	direct	indirect	total
		RAD_A			RAD_B	
Ampsum	0.010**		0.010**	-0.001		-0.001
	(0.00)		(0.00)	(0.00)		(0.00)
Equal	-1.032***	0.017	-1.015***	-0.226***	-0.001	-0.227***
	(0.13)	(0.02)	(0.13)	(0.08)	(0.00)	(0.08)
Humans	-1.658***	0.061*	-1.597***	-0.162	-0.006	-0.167*
	(0.16)	(0.03)	(0.16)	(0.10)	(0.02)	(0.10)
Constant	2.032***			0.615***		
	(0.08)			(0.05)		
var(e.rada)	0.839***			0.342***		
	(0.07)			(0.03)		
var(e.ampsum)	166.436***			167.819***		
	(13.80)			(13.98)		

*p<0.10,** p<0.05, ***p<0.01

4.0.4 Testing Hypothesis 4: Consistency across measures

Table (10) reports the results for regression (1) for the most relevant indicators emerged in section (4.0.1) and our measure of valence derived from face-reading, along with the results of the test proposed by [28] at the bottom. There is evidence of U-shaped relationship between Meantonic and Valence especially in hybrid market (while no evidence emerge in the Human conditions). On the other hand, we cannot observe a U-shape relationship for Ampsum and Eda Symp, for which it appears to be a U-inverse shaped relationship.

Table 10: Consistencies across facial and pyshio measures

Humans

	Meantonic	*Ampsum*	Eda Symp
valence	-18.149***	113.496**	30.742
	(5.59)	(55.69)	(23.15)
valence^2	-77.701	868.582	296.068
	(117.20)	(1166.76)	(485.03)
H_0 : U-shape or Monotone vs Inverse U-shape	✓		
H_0 : Inverse U-shape or Monotone vs U-shape		✓	✓
p-value	0.359	0.279	0.302

Equal

	Meantonic	*Ampsum*	Eda Symp
valence	0.706	20.781	-17.148**
	(1.77)	(23.79)	(7.38)
valence^2	157.675***	-1231.832***	-407.678***
	(24.43)	(327.76)	(101.61)
H_0 : U-shape or Monotone vs Inverse U-shape		✓	✓
H_0 : Inverse U-shape or Monotone vs U-shape	✓		
p-value	0.00001	0.008	0.0002

AI-Majority

	Meantonic	*Ampsum*	Eda Symp
valence	8.146***	113.910***	31.316***
	(1.09)	(14.21)	(6.82)
valence^2	33.343***	-465.542***	-63.931
	(7.84)	(102.11)	(49.00)
H_0 : U-shape or Monotone vs Inverse U-shape		✓	✓
H_0 : Inverse U-shape or Monotone vs U-shape	✓		
p-value	0.019	0.049	
Extreme value outside the boundaries (Trivial Fail to reject H_0)			✓

5 Conclusions

In this paper, we investigated the emotional responses of human traders in hybrid financial markets, specifically focusing on the effects of artificial agents on these emotions and overall price dynamics. We designed an experiment involving three distinct market conditions: a dominated by artificial agents (AI-Majority), a market with an equal mix of human and artificial agents (AI-Equal), and a market with only human traders (Humans). Importantly, emotions were measured using three different methods: self-reported measures, physiological responses, and facial expression analysis. Our aim was to examine the occurrence and magnitude of price bubbles under different conditions, along with the consistency of measurements of emotions.

Our findings reveal that human traders experience milder emotional responses and higher levels of engagement when interacting with artificial agents. Our study also demonstrates that negative emotions can indirectly reduce the formation of price bubbles, highlighting the complex relationship between emotional states and market behavior. Consistency across different emotional measurement methods was moderate, with self-reported measures being the least consistent, highlighting the importance of using multiple methods to obtain a comprehensive understanding of traders' emotional states and their impact on (financial) markets.

6 Supplementary information

For each subject, the EDA is dowsampled to 50Hz and Z-scoring normalization is performed. Then, the cvxEDA algorithm ([29]) is applied to decompose the signal into tonic and phasic components, as well as the underlying sudomotor nerve activity (SMNA). The tonic represents the slow-varying component reflecting the general psychophysiological state of the subject, while the phasic are the fast response to arousing stimuli. To extract the information from both phasic and tonic components, for each experimental condition (i.e., resting-state and trial sessions), we estimate the maximum value of the tonic component (*maxtonic*), its standard deviation (*stdtonic*), and mean value (*meantonic*) using a 20s-long sliding window with no overlap. Furthermore, we estimate the maximum value of the phasic component (*maxphasic*), its standard deviation (*stdphasic*), and mean value (meanphasic), the sum of SMNA peaks (*ampsum*), and their maximum amplitude (*smnnapeak*) within a 5s-long sliding window with no overlap. To obtain a set of features representative of each experimental condition, we calculate the average value of each estimate across all the time windows within both the resting-state and each trial session. Finally, we compute EDAsymp, which is the EDA power spectrum in the (0.045-0.25)Hz band ([30]), over the entire duration of each experimental condition. Regarding PPG, we apply a zero-phase band-pass IIR filter in the (0.5-2)Hz frequency range. Subsequently, we detect peaks in the signal using the multiscale peak and trough detection (MSPDT) algorithm ([31]). The results of this procedure are visually inspected, and any inaccurately identified peaks are manually corrected whenever possible. We import peak-to-peak (PP) distances into Kubios HRV ([32]) and derive the pulse-rate variability (PRV) time series after uniform interpolation at 4Hz. The PRV data is further refined to account for artifacts, such as ectopic beats and abnormal PP values, through the Kubios automatic artifact correction algorithm, utilizing a conservative threshold ([32]). Lastly, for each experimental condition, we fully characterize the PRV computing these features in the time, frequency, and nonlinear domain: *meanrr* (i.e., the mean distance between consecutive peaks); *stdrr* (i.e., the standard deviation of PP intervals); *rmssd* (i.e., root mean squared differences of successive PP intervals); *pnn50* (i.e., the percentage of successive PP intervals differing more than 50 ms); lf (i.e., low-frequency spectral power in the band (0.04-0.15)Hz) and *lfnu* (i.e., the LF power normalized by the power in the band (0.04-0.4)Hz); hf (i.e., high-frequency spectral power in the band (0.15-0.40)Hz) and *hfnu* (i.e., the HF power normalized by the power in the band (0.04-0.15)Hz); the lf_hf given by the ratio between lf and hf; sd1, sd2 (i.e., the standard deviations of the Poincaré plot). Additionally, we combine EDA and PPG information to estimate the ratio between *EDAsymp* and *hf* (EDAsymp_HF), and between EDAsymp and hfnu (*EDAsymp_HFnu*), respectively, i.e., two indexes reflecting the balance between sympathetic and parasympathetic nervous system activity.

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