Emotional State and Market Behavior

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Abstract

We consider the dynamic relationship between emotions and asset market activity. We create experimental asset markets with the structure first studied by Smith, Suchanek and Williams (1988), which is known to generate price bubbles and crashes. To track traders' emotions in real time, we analyze participants' facial expressions with facereading software before and while the market is operating. We find that a positive emotional state predicts purchases and overpricing. Fear predicts low prices, price decreases, and selling. The experiments confirm the intuition that emotions and market dynamics are closely related.

1. Introduction

The connection between asset market price movements and emotions has been widely accepted in popular press and commentary. The supposed existence of fear and exuberance as influences on prices is reaffirmed with great frequency in such quarters. Positive emotion is generally associated with booms and high price levels. Alan Greenspan, while chairman of the Federal Reserve, famously remarked that the American stock market exhibited an "irrational exuberance" when it experienced a rapid run up in 1996. The remark betrayed a belief on his part that the increase had, in part, an origin in positive emotions of traders.[1] Galbraith (1984) describes stock market price bubbles as "speculative *euphoria*". On the other hand, fear is associated with price variability and cited as a force leading to selloffs and price declines. Market volatility indices such as the CBOE's VIX, an index of option prices, are referred to colloquially as "fear" indices. The legendary investor Warren Buffett (2008) writes, "A simple rule dictates my buying: be fearful when others are greedy and be

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[1] Our notion of happiness is a short-term emotional state, as distinct from a longer-term, more stable state of well-being. Bernanke (2012) clearly articulates this distinction. Happiness is a "Short-term state of awareness that depends on a person's perceptions of one's immediate reality, as well as on immediate external circumstances and outcomes. By "life satisfaction" I mean a longer-term state of contentment and well-being that results from a person's experiences over time."

greedy when others are fearful", associating the presence of fear in the market with profitable opportunities to make purchases.

There is data supporting the contention that traders' moods can lead to price movements at the market level. Hirshleifer and Shumway (2003) find that good weather is correlated with higher stock returns, while poor weather does not lower returns compared to average weather. They presume that the mechanism whereby this effect operates is through the positive effect that weather has on mood. Kamstra et al. (2003) observe that returns are relatively low in the dark seasons of fall and winter and appeal to a similar intuition to explain their results. Sports scores seem to matter for financial returns (Edmans et al., 2007), with home team wins translating to higher prices. Bollen et al. (2010) find that Twitter mood predicts subsequent stock market movements. Gilbert and Karahalios (2009) find that the level of anxiety of posts on the blog site Live Journal predicts price declines. In all cases, more positive emotional states are associated with higher prices.

In this paper we focus on the connection between trader emotions and extreme pricing episodes: asset price bubbles and crashes. We use an experimental approach, which exploits the fact that bubbles and crashes can be reliably created and studied in the laboratory. The bubble and crash pattern was first observed in the laboratory with a paradigm introduced by Smith et al. (1988). Subsequent authors have replicated and established the robustness of this price pattern, and the Smith et al. (1988) design has become the dominant experimental paradigm for studying bubbles and crashes. We adhere to this design in the work reported here, and it is described in section three.

Bubbles can be eliminated in this setting when participants are inexperienced, but it typically requires either a very strong framing that deemphasizes the importance of speculative possibilities or a considerable degree of specialized instruction. The magnitude of bubbles is sensitive to environmental parameters such as the amount of liquidity available (Caginalp et al, 1998), institutional factors such as the ability to sell short and the trading institution (Van Boening et al., 1993; Haruvy and Noussair, 2006; Lugovskyy et al., 2012), and the time path of fundamentals (Noussair et al., 2001; Noussair and Powell, 2010; Kirchler et al., 2012; Giusti et al., 2012; Breaban and Noussair, 2014). Nonetheless, there is considerable variation within all conditions that is unexplained. That is, some sessions generate larger bubbles than others despite identical economic structure. We consider here whether variation in the emotional state of participants between different cohorts can account for some of this heterogeneity.

In our experiment, we use face reading software to track the emotional state of all traders, as captured in their facial expressions. The software provides measures of happiness, surprise, anger, disgust, sadness, fear, neutrality, and overall emotional valence. According to Elster (1998) emotions can be differentiated from other mental states on the basis of six features: cognitive antecedents, intentional objects, arousal, valence, action tendencies, and physiological expressions. The work we report here focuses on the last feature, the physiological, as manifested in facial expressions. We consider several issues. First, at the market level, we study how emotional factors can influence the magnitude of bubbles. We test the hypotheses that a positive emotional state on the part of traders before a market opens predicts higher prices, and that fear predicts lower prices. At the individual level, we consider which emotions[2] are linked to better performance, and explore the relationship between loss-averse decision making and emotional state. While the market is operating, we track the bidirectional relationship between specific emotions and overall valence on one hand, and individual decisions and market price movements on the other. While our hypotheses concern overall valence, fear, and neutrality, we also consider whether the other emotions correlate with market activity. Other than one recent study on individual decision making (Nguyen and Noussair, 2014) and one of ultimatum games (van Leeuwen et al., 2014), this paper represents, to our knowledge, the first application of face reading in either economics or finance.

We find a number of strong relationships between emotions, as measured in traders' facial expressions, and market behavior. Positive emotion is associated with higher prices and larger bubbles. The more positive the valence of the emotions a group of traders exhibits before the market opens, the higher prices are in the subsequent market. Individuals in more positive emotional states are more likely to make purchases, but the effect is specific to those who trade, irrationally, on momentum. Fear on the part of traders before a market opens is predictive of low prices. At the individual level, fear is associated with sales, and again, the link is specific to momentum traders. Those who exhibit more neutrality during a crash earn greater profits. We also observe a strong correlation between fear and loss aversion, as registered in a loss aversion measurement task administered before the market opens. In general, the connection between market behavior and emotion is close with causal relationships in both directions.

2. Previous experimental literature on emotions and markets

Moods have been linked to behavior in a number of well-known experimental paradigms, and some of these involve markets. For example, positive moods can influence product choices (Meloy et al., 2000) and bidding in random nth price auctions (Capra et al., 2010). Johnson and Tversky (1983) argue that a positive mood tends to make beliefs more optimistic in the sense that probabilities associated with positive events become distorted in a positive direction. This would push individuals to make less risk-averse choices when they are more positive emotional states. This suggests one mechanism whereby emotional state could influence market behavior. Asset markets involve the trading of a risky lottery and thus more risk-averse agents would tend to place lower value on the asset, and their activity would lead to lower demand and prices. Indeed, Breaban and Noussair (2013) find that more risk-averse cohorts of traders tend to generate lower prices in experimental asset

[2] By emotion, we refer to short-term affective states. This is a distinct, though related, notion to that of mood. See Capra (2004) for a discussion. While moods are affective states of relatively low-intensity, diffuse, enduring and typically without a salient antecedent cause, emotions are more intense and short lived, and they usually have a proximate cause.

markets. Fellner and Macjekovsky (2007) find that risk aversion on the part of a group of traders is associated with lower trading volume. Bosman and Riedl (2003) find that negative mood increases bidding in first-price sealed bid auctions, which is consistent with exhibiting more risk averse behavior. Lowenstein et al. (2001), surveying a large body of research in psychology, argue that a direct link exists between decision making under risk and emotional state.

Fear, in particular, has been associated with risk aversion in a number of studies. Lerner and Keltner (2003) find that fear is associated with pessimistic risk assessments and anger with optimistic ones. Since pessimistic risk assessments lead to more risk-averse decisions with respect to objective risks, fear correlates positively with risk aversion. Kugler et al. (2012) obtain similar results in a different impersonal lottery based task. Nguyen and Noussair (2013) also find that fear in facial expressions is positively correlated with risk averse choices.

We are aware of three previous studies that explore the role of emotion in generating bubbles in experimental asset markets. All three papers consider markets with the structure of Smith et al. (1988), as we do here. Andrade et al. (2012) induce mood exogenously with film clips before the market opens. Subjects watch video clips that are (a) exciting, pleasant and arousing, (b) neutral, (c) fearful, or (d) sad. They find that the pleasantly exciting video clips are associated with larger bubbles than the other three treatments. The other three conditions are not different from each other in terms of average asset prices.

Lahav and Meer (2010) conduct an experiment with two treatments, which they call the positive and neutral treatments. Like Andrade et al., they induce mood by showing film clips to subjects before the market opens. Positive effect was induced with routines by comedian Jerry Seinfeld, and in the neutral treatment, no clip was shown. They find that the positive treatment is characterized by greater bubbles and higher prices than the neutral treatment, though the neutral treatment nonetheless generated price bubbles.

Hargreaves-Heap and Zizzo (2011) conduct an experiment in which emotions are tracked over the course of the session. They focus on anger, anxiety, excitement and joy. They have four conditions. In all conditions, subjects participate in two asset markets. In two of the treatments, individuals rate, on a Likert scale from 1 – 7, how intensely they currently feel each of the four emotions. In one of these conditions, subjects can chat with each other, and in the other they cannot chat. Hargreaves-Heap and Zizzo report that eliciting emotions does not in itself have an effect on market prices, but they do find that the level of excitement reported is positively correlated with price level. They also find that buying assets is linked to excitement and selling assets is connected to anxiety. They do not find a correlation between emotional state and trading profits. The work of Andrade et al. (2012), Lahav and Meer (2010), and Hargreaves-Heap and Zizzo (2012) serves as the source of our first hypothesis, described in section four, that positive emotional valence on the part of traders is associated with higher prices.

3. The experiment

3.1 Experimental design

The structure of the market was based on the paradigm created and studied in Smith et al. (1988). The asset that was exchanged in the market had a finite lifespan of T periods. At the end of each period $t \in \{1,\ldots,T\}$, each unit of the asset paid a dividend d_t that was independently drawn from a distribution that was identical for all periods. In any period t the expected dividend $E(d_t)$ on a unit of the asset was equal to the expected value of the dividend distribution. Dividends were drawn independently in each period. Therefore, the expected future dividend stream at time t, $E[\sum_t^T d_t]$, equaled the expected period dividend multiplied by the number of periods remaining in the life of the asset. In other words, $E[\sum_t^T d_t]$ = $(T - t + 1)E(d_t)$.

Since dividends were the only source of intrinsic value for the asset, the fundamental value f_t had a particularly simple structure. It was equal, at any time t, to the expected future dividend stream from time t onward. In other words, $f_t = (T - t + 1)E(d_t)$. In our markets, the life of the asset was T = 15, and the dividend was $d_t \in \{0,8,28,60\}$, where each realization was equally likely, for all t. Thus, $E(d_t)$ = 24, and $f_t = 24(16 - t) = 384 - 24*t$ at time t. The dividend distribution had a standard deviation of 27 per period, which was greater than the expected dividend. Therefore, risk-averse traders could value the asset at considerably less than its fundamental value.

In each period, each trader had the ability to trade units of the asset for cash with any other trader in an open market, provided that he always maintained non-negative cash and share balances. Transaction prices were determined in a continuous double-auction market (Smith, 1962). This type of market operates in the following manner. Each period, the market is open for a fixed time interval, which was two minutes in this experiment. At any time while the market is open, any trader can submit an offer to sell or to purchase a share. These offers are posted publicly on all traders' computer screens. Also at any time, any trader can accept an offer that another trader has submitted. When a bid or ask is accepted by a trader, a transaction for one share takes place between the trader who posted the offer and the trader who accepted it. Thus, within a period, it was possible for different transactions to occur at different prices. An individual could trade as much as he wished provided he has sufficient cash and units of the asset to complete the trades.

Each subject had an identical portfolio, consisting of an initial endowment of 5 units of asset, and 5000 units of experimental currency, at the beginning of period 1. A subject's final earnings in the market were equal to the cash he had at the end of the experiment, which corresponded to his initial cash, plus the value of dividends received, plus (minus) any profit (loss) from trading. The market was computerized and used the Ztree program developed at the University of Zurich (Fischbacher, 2007).

Prior to the opening of the asset market, we administered the loss aversion measurement task used by Trautmann and Vlahu (2007), which is based on an earlier protocol of Fehr and Goette (2007). This task consisted of a series of six choices, presented in a price list format. Each choice offered the opportunity to play a gamble which paid 4.5 Euro with probability .5 and either -0.5, -1.5, -2.5, -3.5, -4.5 or -5.5 Euro with probability .5, with each choice appearing exactly once. Subjects were required to indicate whether or not they accepted to play each of the six gambles. The number of gambles one decided not to play is interpreted as a measure of her loss aversion.

Subjects completed the task using pen and paper. They submitted all six of their decisions simultaneously when they turned in their completed sheet of paper to the experimenter. They were informed prior to beginning the task that only one of the decisions would count toward their earnings. After all decisions were turned in, a die was rolled. The outcome of the roll determined which decision would count for each participant. If a subject had chosen not to play the relevant gamble, she received a payoff of zero for this part of the experiment. If a participant chose to accept the selected gamble, a coin was flipped to determine whether she received 4.5 Euro or the negative payment specified in the gamble.[3] A separate coin was flipped for each participant who chose the gamble.

3.2. The Facereader software

During the sessions, all subjects were videotaped and the videotapes were analyzed later with Noldus Facereader. The taping began at least 30 seconds before the opening of the market for the first period and continued continuously until the session ended.

Facereader operates in the following manner. The position of the face in an image is found using a method called the Active Template Method (ATM). This method places a template over an image and calculates the most likely position of the face. A second algorithm for face finding, the Viola Jones cascaded classifier algorithm, takes over when the Active Template Method cannot locate a face. A model called the Active Appearance Model (AAM) describes the location of 530 key points in the face and the facial texture of the convex hull defined by these points. The model uses a database of several thousand annotated images and calculates the main sources of variation found in the images. Principal Component Analysis is used to reduce the model's dimensionality. The classification of the facial expressions is done with an artificial neural network, which takes the vector of 530 locations on the face as input. The network was trained with several thousand images of different individuals to classify the extent to which a face expresses the six basic universal emotions of happiness, surprise, anger, disgust, sadness and fear, as well as neutrality.

[3] Some subjects experienced real losses in this part of the experiment. However, they were informed that there would be subsequent activities in the session in which they could expect to earn money on average. No subject ended the session with negative final earnings, because income in the market phase of the experiment in all cases more than fully offset losses incurred in the loss aversion measurement task.

The output of Facereader is in terms of graphics and text. This software´s quantitative output is a vector of values for the seven emotions and an overall valence of emotional state. The possible values of each emotion range from 0 to 1, and valence ranges from -1 to +1. The values are registered five times per second. Figure 1 illustrates an example of the output of Face Reader graphically. As the video is analyzed, the two charts on the right of the figure indicate, in real time in both bar graph and time series format, the extent to which each of the six basic emotions (as well as neutrality) is reflected in the facial expression. A pie chart, in the lower portion of the figure, shows the average intensity of each emotion. These values are normalized so that the sum over all emotions equals 1. The valence is an overall measure of whether the individual's emotional state is currently positive or negative. It is given as a time series in the upper middle portion of the screen. The measure compares the conformity of the facial expression to 'Happy', the only positive emotion, with that to the four negative emotions. Facereader output tends to identify the intended emotion of an individual with a high degree of success (Uyl and Kuilenberg, 2005). It also corresponds closely to specialist observers' evaluations of the faces considered (Terzis et al., 2010; Lewinski et al., 2014).

[Figure 1: About Here]

This is the first study to employ face reading in experimental finance. In our opinion, face reading is especially well-suited to the study of emotions for several reasons. The first reason is that it classifies an individual's physiological state along emotional dimensions in a quantitative manner. This allows us, for example, to claim that one stimulus provokes more disgust but less sadness than another, or that a particular decision is taken when an individual is surprised rather than angry. A second advantage is that it registers emotional measurement in a manner that is completely unobtrusive to the participant, and data acquisition would proceed unnoticed if the individual were not informed that it was occurring.[4]

The third reason is that the facial expressions corresponding to the six basic emotions appear to be universal (Ekman and Friesen, 1984). These expressions accompanying these emotions are common to all cultures and primates (Ekman, 1997). They are the same for blind and sighted individuals (Matsumoto and Willingham, 2009), which provides strong evidence that they are innate. This means that results of studies such as ours should be replicable in different population groups and cultures. Happiness is positive in valence, surprise is neutral, and the other four are negative. Happiness and anger are approach emotions, which tend to lead an individual to move toward the situation that triggers the emotion. Sadness, disgust, and fear, are withdrawal emotions, meaning that an individual typically seeks to avoid the stimulus that induces these emotions.

[4] Subjects were aware that they were being videotaped but not that there videotapes were to be analyzed with facereading software.

3.3. Structure of the data

Our dataset consists of 13 sessions. The sessions were conducted at Tilburg University and all subjects were students at the university. Subjects were recruited via an online system. No subject participated in more than one session of the experiment. On average, the sessions lasted one hour. Between six and 11 traders participated in each session, with an average of eight subjects per session. Participants' earnings from the asset market were converted to Euro at a rate of 500 units of experimental currency to 1 Euro. This resulted in an average payment of 15.6 euros (including the loss aversion measurement task).

The market data consist of submitted bids and asks, and trades, which are acceptances of bids and asks. We have market data for 15 periods in each session. We also have the emotion data from all 13 sessions for the two minutes before the market opened in period 1, and during the crash period, defined as the period within a session in which the greatest price decrease occurred. However, for a purely technical reason, we only have complete real time data for five of the 13 sessions. Due to an improvement introduced in the video quality in late 2013[5], which increased the speed that the analysis could be conducted, in these five sessions it was possible to analyze all videos for the entire duration of the experiment. Therefore, for all 50 subjects participating in these sessions was possible to match their trading activity with their emotional responses. This allows for an analysis of the dynamics between emotions and asset market behavior establishing causal relationships both at individual level and market level.

The data are organized by two different lengths of time interval. The first is in 10 second intervals, which means that a session contains a total of 202 intervals. The data are in panel data format in which 50 subjects are the cross-sectional data, and each 10 seconds interval is an observation. The reason for specifying blocks of 10 seconds is that it is somewhat greater than the typical time course of emotional reactions. Emotions arise as a consequence of some events and last for a few seconds. There is little evidence in the literature on emotion duration, but Sonnemans and Frijda (1994) find that it depends to a great extent on the intensity of the emotion. Scherer et al (1986) find that different emotions tend to have different duration and they classify sadness as the most lasting one, followed by joy, anger and fear. Given that the market experience is relatively short and making decisions might take up to a few seconds, we expect that a 10 second interval is enough to capture both emotional and behavioral reactions to specific market events as well as short enough to capture the reaction to current activity only. Each emotion variable (happiness, fear, anger, disgust, sadness, surprise, neutral and valence) was averaged every 10 seconds beginning with the market opening, so that the 300 observations that Facereader software provides in ten seconds (30 per second) were averaged for each subject. We will refer to the unit of time in this data set as an *interval*.

[5] New video cameras with higher resolution were used.

The second time scale on which we organized the data was in terms of the trading *period*, as is typical in experimental work. We construct a data set that has observations for each of the 50 subjects during 15 periods. In this case the emotion variables were averaged over the 120 seconds of each period and subject. In our presentation of the data, intervals are indexed by s= 1,…, 202, and periods by t = 1,…,15.Tables 1a and 1b below show the mean and standard deviation of emotions across subjects and across time span for both data sets.

[Tables 1a and 1b: About Here]

3.4 Trader types

In some of analysis, we distinguish different types of traders using the classification introduced by DeLong et al. (1990) and employed for the analysis of experimental markets by Haruvy and Noussair (2006) and Haruvy et al. (2014). They classify traders into three types, called *Fundamental Value* Traders, *Momentum* Traders, and *Rational Speculators*. We classify each of the traders participating in our experiment as one of the three types, according to the following criteria.

We define an individual's behavior as consistent with the *Fundamental Value* Trader type in period *t* if either one of two conditions holds. The first condition is that, if $p_t > f_t$, then $s_{it} < s_{i,t-1}$, where p_t is the average price in period *t*, f_t is the fundamental value in period *t*, and s_{it} is the number of units of asset that individual *i* holds in period *t*. This means that if prices are above fundamentals, trader *i* is a net seller of units in period *t*. The second condition is that if $p_t < f_t$, then $s_{it} > s_{i,t-1}$. If prices are below fundamentals, trader *i* is a net buyer in period *t*. The fundamental value trader, then, acts as if she is using the fundamental value as a limit price.

A trader's behavior is consistent with the *Momentum* Trader type if either of two conditions holds. The first is that, if $p_{t-1} < p_{t-2}$, then $s_{it} < s_{i,t-1}$. The second is that, if $p_{t-1} > p_{t-2}$, then $s_{it} > s_{i,t-1}$. The momentum traders is a net purchaser in period *t* if there has been an increasing price trend in the last two periods, and sells off units if there has been a decreasing trend.

A trader's behavior is consistent with the *Rational Speculator* Trader type if her behavior in period *t* satisfies one of the following two conditions. The first is that, if $p_{t+1} < p_t$, then $s_{it} < s_{i,t-1}$, and the second is that, if $p_{t+1} > p_t$, then $s_{it} > s_{i,t-1}$. This type of agent anticipates the price in the next period in an unbiased manner. She makes positive net purchases if the price is about to increase between the current and the next period. She makes net sales if the price is about to decrease.

To classify a subject as one of the trader types, we count the number of periods during which a person is consistent with each type, and then classify him as the type with which he is consistent for the greatest number of periods. If there is a tie between two types, we classify the trader as belonging to each type with proportion .5. If there is a tie between all three types, he is assigned each type with proportion .33.

4. Hypotheses

We advance several hypotheses about the relationships between emotions and market behavior. Most of the hypotheses emerge from previous work. This first is suggested by the previous studies of Lahav and Meer (2010), Andrade et al. (2012) and Hargreaves-Heap and Zizzo (2012). We hypothesize that the more positive the emotions that traders exhibit before a market opens, the greater the price level in the market. Thus, we hypothesize that positive emotion is positively related to subsequent price, and thus in all likelihood within our setting, to greater bubbles. This pattern is also suggested by previous work on auctions, which concludes that positive mood is associated with higher bidding (Capra et al., 2010).

Hypothesis 1: More positive initial emotional valence on the part of the average trader before the market opens predicts greater subsequent prices and a larger bubble.

To test this hypothesis, we check whether there is a correlation between (a) the average emotional valence within a group of traders in the 30 seconds before their market opens for period one, and (b) the average price over the 15 periods the market is open. Valence is a measure of net positivity of emotional state.

We also consider whether fear predicts lower prices. That it should do so is intuitive. However, Andrade et al. (2012) fail to detect such an effect, and their attempt to induce fear generates similar results to a market in which emotions were not induced. However, Hargreaves-Heap and Zizzo do find that anxiety, a closely related emotional state, is correlated with lower prices. To the extent that fear is associated with risk aversion (see Lerner and Keltner, 2001, or Nguyen and Noussair, 2014), fear would lead to lower pricing of the lottery that corresponds to the price of the asset. Furthermore, it is possible that those who experience fear would be less likely to take on the risk associated with speculation, speculative demand would be reduced, and fear would have the effect of lowering prices.

Hypothesis 2: Greater fear on the part of the average trader before the market opens is correlated with lower subsequent prices.

The first two hypotheses consider the initial emotional state of traders, which is not being influenced in any way by the market activity itself. Uncontaminated valence and fear measures are related to the magnitude of the bubble later in the market session. The following hypothesis considers the predictive power of emotions on pricing behaviour within session. For this purpose, the average emotions and the average transaction prices are considered for each of the 15 periods in which the market operates. Following up on hypotheses 1 and 2, we further investigate whether positive emotional state helps sustain higher prices over time and if fear is a harbinger of lower prices in the immediately subsequent periods. We hypothesize that that more positive emotional state would on average predict higher prices in the following periods and that more fear in one period would predict decreasing average prices in the next..

Hypothesis 3: At the market level, more positive average emotional state on the part of market participants predicts price increases and more fear predicts price decreases in the next period.

Furthermore, at the individual level, positive valence may lead purchases at the individual level, due to more optimistic beliefs or a less risk averse attitude generated by a positive emotional state. This conjecture is in line with the affective generalization hypothesis of Johnson and Tversky (1983) that addresses the role of affect in judgments of probabilities. They argue that negative emotions trigger more pessimistic risk assessments, while positive emotions entail more positive risk assessments, and this leads individuals in a more positive mood to take more risk. Following this argument, we hypothesise that a positive emotional state at any time in the market will cause greater net purchases of asset, which is in effect a lottery, in the ten seconds immediately afterward.

Hypothesis 4: A more positive emotional state makes individuals more likely to make purchases in the subsequent time interval.

We now focus on the individual behavior driven by fear. The psychological implications of fear being a withdrawal emotion are that individuals will tend to avoid the situation that produces this emotion. Therefore, fear in the experiment is caused by the perceived riskiness of an asset, if a trader would try to avoid that risk, she would reduce her inventory by making sales.

Hypothesis 5: More fearful individuals will be more likely to make sales in the subsequent time interval.

The next topic we consider is the relationship between emotions and trader types. Emotions could have different effects on a trader’s behavior depending on the trader type. For example, we might expect that momentum traders, who behave irrationally and earn less money than the other two types (see Haruvy and Noussair (2006) or Haruvy et al. (2013)), would be more influenced by emotions when trading, while fundamental value traders and rational speculators, who typically earn more would be less swayed by emotions. Breaban and Noussair (2014), when correlating individuals´ characteristics and their trading strategies, found that higher cognitive ability was positively correlated with the fundamental value trader type and negatively correlated with momentum trader type.

Cognitive ability is positively correlated with earnings in experimental asset markets (Corgnet et al., 2014; Charness and Neugebauer, 2014; Breaban and Noussair, 2014). Lo et al. (2002) and Lo and Repin (2005) find that emotional individuals achieve lower earnings in the stock market. On the other hand, Coates (2012) documents how emotions are closely linked to stock trading, and a number of authors have argued that emotional responses generally are beneficial for decision making (Damasio, 1995).

Hypothesis 6: Momentum traders´ purchase and sale decisions correlate with emotions more than those of fundamental value traders or rational speculators.

Besides purchases and sales, there are other behavioral patterns in the market that could be explained by emotions. The decision to submit offers to buy or to sell might also depend on the emotional state of traders. It seems reasonable to believe that if traders base their trading decisions at least partly on emotions, more neutrality on the part of traders would lead them to be less active in the market. That is to say, more emotional agents will intervene more by submitting offers to sell or offers to buy. Our next hypothesis, therefore, would be that this pattern would appear in the individual level data.

Hypothesis 7: More neutral individuals are less active in the market, in that they submit fewer offers.

Hypothesis 1 to 6 dealt with the effect of emotions on individual decisions, such as sales, purchases or submission of offers, as well as market outcomes. However, it seems likely that in turn, decisions and their subsequent outcomes have an impact on traders´ emotional state. Our next two hypotheses are about the effect of market activity on emotions. A straightforward intuition is that more positive emotional state results when the overall financial position, in terms of expected final earnings, of a trader improves.

Hypothesis 8: A better overall financial position is correlated with a more positive emotional state.

On the other hand, traders could also have short-term emotional responses to specific actions such as buying and selling and the extent to which a purchase or sale has been profitable or not. These responses may serve to reinforce the strategies that led to the profitable transaction. While it might be natural to hypothesize as well that unprofitable transactions lead to negative emotions, we believe that this effect is not obvious. If an individual realizes that the trade is unprofitable, negative emotions might result. However, the party to a voluntary trade might believe it to be profitable, when in fact is not. In such cases the individual might experience positive emotion. Thus, in our view the effect of unprofitable trades on emotions is ambiguous. Thus our eighth hypothesis is restricted to profitable transactions.

Hypothesis 9: A profitable trade has a positive immediate impact on emotions.

Our final hypothesis, ten, concerns the emotional correlates of crashes, and consists of three parts. The first has to do with the overall strength of emotions during a crash and trader profits. Lo and Repin (2002) and Lo et al. (2005) find that those who exhibit less volatility in their emotional state in the face of fluctuations in the market have better trading performance. In our experiment, the analogy would be a hypothesis that the level of neutrality in one's facial expression during a crash is correlated with greater trading profits.

Hypothesis 10: Traders who exhibit greater neutrality during a crash achieve greater earnings.

5. Results

5.1. Market Price Patterns

The time series of transaction prices in each of the 13 sessions are shown in figure 2, along with the time path of fundamental value. In the figure, the vertical axis is in terms of experimental currency, and the horizontal axis indicates the market period. As can be seen in the figure, there are large differences between sessions, but in most sessions the bubble and crash pattern is observed. Typically, prices remain above fundamental values for a considerable period of time, and then exhibit a rapid fall toward fundamental value. [6]

[Figure 2: About Here]

5.2.The influence of emotions on market activity

We now evaluate the hypotheses advanced in section four. Six of the hypotheses concern how valence and fear are harbingers of market price movements at different time horizons. The first two

[6] The facial expression data exhibit several broad characteristics. The first is that the valence is typically negative. This likely means that participation in experiments yields disutility for participants compared to other activities. There is great volatility in emotional state even over short time intervals. This may reflect the large number and heterogeneity of events that one experiences in a period. There is no discernible decline in the overall strength of emotion over time, over the roughly 35-minute period the asset market is in progress. Anger tends to be greater at the outset, possibly reflecting the fact that individuals who are concentrating tend to look like they are angry (see Zaman and Shrimpton-Smith, 2006), but within a few minutes it stabilizes. Valence reflects this pattern, typically being very negative at the very beginning of a session but stabilizing at a moderately negative level for the rest of the session.

hypotheses are about the relationship between the initial emotional profile and the overall price pattern, and are summarized as results 1 and 2.

Result 1: A more positive emotional state before the market opens is positively correlated with subsequent market price level.

Support for Result 1: We take the average valence that Facereader measures over the 30-second interval before the market opens for each subject. We then average it for all subjects in a session. Then we correlate the average for a session with the average amount that price exceeds fundamental value over the course of the session[7]. Figure 3 below plots the average initial group valence against the average price level over the 15-period life of the asset. The figure shows a clear positive relationship between emotional state and price. The Spearman correlation between valence in a session and average price level in the session is ρ = 0.6190 (p = .01).[8] □

[Figures 3 and 4: About Here]

Result 2: Average trader fear before the market opens is negatively correlated with the subsequent price level in the market.

Support for result 2: The relationship between the average fear a cohort expresses before the market opens and price level over the subsequent market is very pronounced. Figure 4 relates the fear that Facereader registers in the average trader in a given session to the average price in the session. The figure shows a strong negative relationship between the two variables. The correlation is highly significant (ρ = -0.8333, p = 0.01). □

Each of the other emotions considered separately also correlates with subsequent price level. The other three negative emotions, sadness, anger, and disgust, correlate negatively with price level at ρ = -.381, -.428, and -.333, respectively, while happiness and neutrality correlate positively with price level at ρ = .476 and .357. While none of these correlations are significant, they are consistent with higher (lower) prices being associated with positive (negative) emotional states.

[7] The same results would obtain if we used the average price difference from fundamentals $p_t - f_t$. This difference is referred to as the *Bias* in a market by Haruvy and Noussair (2006).
[8] The correlation between the variance of valence among participants before a session begins, and the volume of trade over the entire session, is .12, and is not significant at conventional levels.

While results 1 and 2 concerned the relationship between initial emotional state and average behavior, result 3 considers the predictive power of emotional state on prove movements while the market is in progress.

Result 3: Fear increases the probability of prices decreasing, while the rest of the emotions decrease the likelihood of a decrease.

Support for result 3: We construct a dummy variable to identify the average price movement across the 15 periods. The dummy takes value 1 if p_t-$p_{t-1} < 0$ and 0 otherwise. We then run a logit model with subject fixed effects using the dummy variable as the dependent variable.[9] Emotions at time t-1 are the independent variables in this model. The table 2 below shows that with more fear on the part of traders, prices in the market are more likely to decrease. On the contrary, neutrality, happiness and anger reduce the odds of this happening.[10] This seems to be in line with Lerner and Keltner (2001) findings about withdrawal emotions such as fear being associated with higher risk aversion, and approach emotions such as happiness and anger associated with risk seeking attitudes. According to this argument, it seems reasonable to think that fearful people who tend to be more risk averse would place a lower value on the asset and therefore lower prices in the market. Those who experience approach emotions give more value to the lottery the asset represents because of a risk loving attitude, leading to increasing prices. Overall valence is not significantly correlated with subsequent price movements.

[Table 2: About Here]

The positive relation between valence and price movements suggests that positive valence is associated with higher demand for the asset and that fear prompts a willingness to sell. As reported in result 4, this is indeed the case

Result 4: Traders with higher valence at time s-1 make more purchases at time s

Support for result 4: In order to determine how emotions affect individual trading activity we run a Poisson count regression with subject fixed effects where the dependent variable is the number of

[9] We test fixed effects vs random effects for this model using the Hausman test (p(chi2)<0) and also the test of over identifying restrictions (p=.043) and they both reject the hypothesis that RE is consistent. Though if we compare the estimates in Table 9 as it is done by Rodriguez and Elo (2002), it seems to be the case that with random effects it is mainly the fear coefficient that significantly changes and becomes highly significant, while for some of the other coefficients the change is not as pronounced. This indicates that estimates from both specifications have some robustness. Rodriguez and Elo (2002) argue that such robustness is typically associated with the consistency of estimates.

[10] It is interesting to mention here that emotions in this case seem to predict price movements' direction but not magnitude. Additional analysis was done to investigate this, but emotions do not appear to have predictive power for how much prices will decrease. More precisely we constructed a variable that measured the magnitude of the price decrease as max[p_t-p_{t-1}, o] and used it as dependent variable in a regression with the lagged values of emotions as independent variables. None of the coefficients were significant.

units a subject has bought or sold during each 10 seconds interval. Each transaction is considered at the time at which a bid or ask has been accepted. In particular we look at the influence of the past overall emotional state controlling for financial position and price level. We find that subjects are more likely to make more purchases in the current interval, the higher valence they exhibited in the previous interval. The left portion of Table 3 shows that introducing the lagged value of purchases in Model 1, higher emotional valence Granger-causes purchases[11]. Another intuitive result from the estimation is that the larger the number of units in inventory, less likely it is for subjects to buy more.

Result 5: More fearful traders at time s sell more units at time s

Support for result 5: The right half of Table 3 reveals that, controlling for the units and cash they had and considering how high average prices are compared to fundamentals, we do not find a significant effect of the lagged value of fear over current sales. This could be due to the fact that, according to previous studies, fear has a shorter duration and it is more volatile than the rest of the emotions. Therefore, capturing the causal relationship between this emotion and subsequent trading activity, considering the restrictions of the data, in this case might not be possible. Instead, we perform the analysis for the contemporaneous level of individual fear as shown by Model 3 and Model 4. We find that fear is indeed related to higher probability of reducing the number of assets in inventory in a given period. On the other hand, contemporaneous valence does not have an immediate effect on purchases in a given period, suggesting a different time lag between positive and negative emotions and the behaviour they trigger. Positive emotional state has a slow impact on purchases, while fear is contemporaneously correlated with sales.

[Table 3: About Here]

We now consider these patterns for each trader type separately. Recall that we hypothesized that the momentum traders were those whose decisions were most likely to be dependent on emotional factors. The other two types, who are more rational, were less swayed by emotion. As we report in result six, we find that is indeed the case.

Result 6: Momentum traders buy more when they are in a more positive emotional state, while there is no correlation between emotions and the number of purchases and sales of fundamental value traders or rational speculator traders.

Support for result 6: As described in section 3, we classify individuals according to their trading strategies into fundamental value traders, momentum traders and rational speculator traders. We

[11] The time series of the valence Granger-causes purchases, since the lagged values of the independent variable provides statistically significant information about future purchases.

observe that 40% are fundamental value traders, 34% are momentum traders and 26% are rational speculator traders. We then analyse how emotions affect their trading behaviour. Table 4 below shows that the momentum types, who are the relatively unsophisticated traders because they buy when prices have been going up and sell when the trend has been negative, both buy and sell based on their emotional state. Their behaviour accounts for the positive relationship between valence and subsequent purchases, as well as between fear and subsequent sales. Thus, hypothesis 6 is supported.

In previous studies it has been noted that relatively unsophisticated traders tend to accept offers made by other traders rather than submitting offers themselves (Menshikov and Plott 1998). This suggests that it may be the momentum traders that are accepting other traders ‘offers to sell at high prices during the bubble. In order to bring some more evidence to support this result, we compute the total number of purchases relative to total number of bids for each type of trader. A higher ratio indicates that subjects are less active submitting offers to the market; that is to say, their trades are being concluded by accepting other participants´ offers. For rational speculators this ratio is 0.49, for fundamental value traders goes up to 0.60 and for momentum traders the ratio is 0.72. The ratio of sales relative to asks is not significantly different between trader types: 0.45, 0.48 and 0.42 respectively. This means that it is mostly the momentum traders accepting offers to sell at high prices in our overpriced markets, which is typically suboptimal behaviour.

[Table 4: About Here]

Result 7: More neutral individuals participate less in the market

Support for result 7: Controlling for the overall financial position of an individual and the market prices, we look at the effect of emotions on submitting bids and asks. We run a logit model where the dependent variable is the number of bids/asks/total number of orders that a subject has made in an interval of 10 seconds.

Table 5 below shows that, at the individual level, more neutrality is associated with less initiation of orders, especially fewer bids. This seems to indicate that individuals who experience more emotions are more active in the market. Including the lagged value of the dependent variable in each model we obtain that neutrality Granger-causes the number of bids and the total number of bids and asks that a trader submits to the market.

[Table 5: About Here]

5.3. Market activity influencing emotions

The previous subsection has shown how emotional valence, fear and neutrality are influences on market behaviour. Positive emotional valence precedes higher prices, and fear precedes lower prices. In this subsection, we study the relationship in the other direction, how emotions result from market activity. The first proposition we consider is that prospective earnings are associated with a more positive emotional state.

Result 8: Greater current wealth is positively correlated with emotional state

Support for result 8: A fixed effects regression in table 6 shows that a more favourable balance of cash and units improves traders' emotional state while higher price level has a negative effect on valence. We define the price level as the difference between the average price and the fundamental value of the asset at any time. Given the emotional state in period s-1, more money and units increase valence in period s, so valence is Granger-caused by these two variables.

It seems straightforward the fact that money and units are positively related to valence since they are an indicator of wealth. Since the prices are always above fundamentals over the course of the sessions, the price level variable here is actually a measure of mispricing. Our results seem to indicate that higher mispricing lowers valence perhaps because traders believe the price trajectory and thus the market value of their assets is not sustainable. This is an interesting finding since our first result in this chapter is that traders with higher valence make more purchases. Therefore the emotional process underlying the formation of a bubble could be that positive emotional state enhances purchases, but as prices increase and traders find themselves in a boom, their emotions become less positive. A Spearman correlation test significant at 1% sustains that the price level variable is negatively correlated with valence (ρ= -.09).

[Table 6: About Here]

It is also natural to think that profitable purchases or sales would improve traders´ emotional state and that bad decisions regarding trading would entail more negative emotions. We hypothesized that the more profitable a purchase is, the higher would be the subsequent valence. As reported in result 9, the hypothesis is supported in our data.

Result 9: Profitable purchases lead to higher valence

Support for result 9: The support for the result is given in the column labelled model 3 in table 7. We define the variable to measure how profitable a purchase is as the difference between the fundamental value of the asset and the transaction price. The estimated coefficient is positive and significant.

The table also shows that, in contrast, the profitability of a sale, as measured by the difference between the price and the fundamental value of the asset, has a negative estimated coefficient. Our conjecture is that it not the profitability of the sale that affects individuals' valence, but finding himself in a high mispricing situation, which we already found to be related to negative emotional state. This interpretation is corroborated by the specifications in the last two columns of the table, which reveal that once the current market price level is taken into account, the significance of transaction profitability vanishes. The price level has a significantly negative estimated coefficient, indicating that higher prices, all else equal, are correlated with negative emotions. This may reflect a realization that the high prices are not sustainable in the long run.

[Table 7: About Here]

[Table 8: About Here]

5.4. Crashes

Of special interest are market crashes. These can be very large and are generally unanticipated by participants (Smith et al., 1988; Haruvy et al., 2007). The relationship between a crash episode and the dynamics of emotion is illustrated in figure 5. The data are from sessions 8 to 13 where the strength of the average level of several emotions that members of the session cohort exhibit over the periods just before and during the crash, is plotted. These emotions are anger, fear, happiness, and surprise. They are normalized at the levels observed in the period previous to the crash. The data show a clear pattern. Sadness and anger exhibit modest increases during a crash as traders' paper wealth declines. However, fear and surprise exhibit sharp increases, as uncertainty increases. By the time the crash is ending, surprise has fallen sharply, and fear has stabilized at high levels. However, sadness and anger continue to increase, as traders realize the extent of the losses the crash has created. The figure illustrates the existence of an emotional reaction to a key market event and the ability of Facereader to coherently characterize this reaction.

[Figure 5: About Here]

Hypothesis ten asserted that more neutrality during a crash is correlated with greater earnings. Figure 6 plots the relationship between the level of neutrality individuals exhibit during a crash period, which we define as the period with the greatest price decrease from the preceding period, and the final earnings an individual accrues over the entire 15-period market. The figure suggests that more neutrality during a crash is correlated with better performance.

[Figure 6: About Here]

Result 10: Traders who exhibit greater neutrality during a crash achieve higher earnings.

Support for result 10: The correlation, at the level of the individual, between her average neutrality during the crash period and her final earnings is 0.205 (p = 0.16). Neutrality correlates negatively with units held at the end of the crash period at ρ = -.27 (p = .064). The other emotions do not correlate with the number of units held, and thus the amount of unrealized capital losses, during a crash. The results are similar if the units held at the beginning of the crash period are considered (very few units are exchanged during a crash because of very low demand). □

5.5. Loss aversion and emotions

The last result describes a strong correlation between loss aversion and fear. The loss aversion protocol that was administered at the beginning of the sessions, and the measurement of the emotional profile of individuals before the market opens, permit an analysis of the correlation between loss aversion and the emotional state of participants at the individual level that is independent of any experience on the market. As summarized in result 11, those who make more loss-averse decisions exhibit more fear in their facial expressions, and have a more negative overall emotional state. There is no correlation between loss aversion and any other of the six basic emotions or with neutrality.

Result 11: Individuals who exhibit more fear make more loss-averse decisions. Loss aversion is not significantly correlated with anger, happiness, sadness, disgust, surprise or neutrality. Loss aversion is negatively correlated with the valence of emotional state.

Support for Result 11: Table 9 contains the correlations between the number of gambles declined in the loss aversion task and the average consistency of facial expressions with each of the six emotions that Facereader registers in the 30 seconds before the market opens. A greater number of gambles declined indicates greater loss aversion. The table shows that the correlation between fear and loss aversion, .3427, is positive and significant at the $p < .05$ level. The correlation between loss aversion and valence is negative (ρ = -.3012, $p < .05$). In contrast, none of the correlations with other emotions are significant at even the 10% level. □

[Table 9: About Here]

6. Conclusion

In this paper, we study the connection between emotions and asset market prices. We find a number of patterns that conform to commonly expressed intuition about the link between emotion and asset prices. When traders are in a more positive emotional state at the time the market opens, asset prices are higher. When they feel more fear, prices are lower. Momentum traders make more purchases when in a relatively positive emotional state m, and then sell when they experience fear. Those who keep a neutral emotional state during a crash earn greater profits. Greater fear on the part of the average participant is a harbinger of a price decrease.

A number of factors have been shown to influence the incidence and magnitude of bubbles in the laboratory. These include the institutional structure, the time path of fundamentals, and the risk aversion, loss aversion, and cognitive ability of traders. The results reported here show that another factor can be added to the list; the emotional state of traders. This finding is in agreement with similar results that have recently been obtained (Lahav and Meer, 2010; Andrade et al., 2012; Hargreaves-Heap and Zizzo, 2012). Thus, it is becoming clear that asset price bubbles in experimental markets are a complex phenomenon, subject to many determining influences.

We find a strong correlation between fear and loss aversion. Such a connection is, in our view, quite natural and intuitive. Those who anticipate that they will have a more negative response to a financial loss exhibit more fear when placed in a situation in which losses are possible, and thus make decisions in such a manner as to minimize the likelihood of their occurrence.

This study is the first application of face reading to experimental finance. This methodology had yielded what are, in our view, coherent results. Our view is that the strength of our results contributes to the validation of the methodology. We believe that Facereading has considerable potential for the study of markets. In starker experimental settings than the one studied here, the emotional response to specific events, such as to a price quote one has received, or to a specific transaction one has made or observed, can be isolated and studied. In particular, in future work, face reading can be used to study face-to-face market transactions. In such situations, facial cues are important sources of information about the intentions and emotional states of other parties to a potential transaction. In these settings, individuals may try to manipulate their facial expression as part of their strategy to obtain more favorable terms. Face reading technology is highly conducive to the study of such behavior.

The finding that emotions influence market behavior has clear policy implications. It shows that there is concrete basis for the idea that central banks and governments must take into account indirect effects of their announcements on the emotional state of market participants and how this might affect market prices. Such effects would arise in addition to the effects of such announcements on the fundamentals of the economy.

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Table 1a: Standard deviation of emotions across subjects and intervals

	Neutrality	Happiness	Sadness	Anger	Fear	Disgust	Surprise	Valence
Observations	10020	10020	10020	10020	10020	10020	10020	10020
Mean	.524	.092	.083	.038	.001	.012	.021	-.029
Std. Dev.	.305	.153	.128	.091	.007	.054	.067	.231

Table 1b: Standard deviation of emotions across subjects and periods

	Neutrality	Happiness	Sadness	Anger	Fear	Disgust	Surprise	Valence
Observations	750	750	750	750	750	750	750	750
Mean	.649	.127	.119	.056	.002	.017	.027	-.030
Std. Dev.	.213	.135	.131	.098	.006	.046	.051	.151

Table 2: Market behaviour: Negative price movements depending on emotions: Comparison for logit/random/fixed effects models (dependent variable at time t)

	Logit	Random Effects	Fixed Effects
Fear $_{t-1}$	402.26	354.45**	98.08
Neutral $_{t-1}$	-5.34	-6.35**	-14.27***
Happiness $_{t-1}$	-5.03	-6.14**	-15.19***
Anger $_{t-1}$	-4.46	-5.40*	-14.30***
Disgust $_{t-1}$	-4.91	-6.17	-20.25***
Sad $_{t-1}$	-2.16	-2.96	-10.68**
constant	5.40	6.46**	

Nr. Observations RE :700

Nr. Observations FE: 546

Table 3: Individual behaviour: trading activity depending on past emotions *(Poisson count regression with subject fixed effects)*

	Buy_s	Buy_s		$Sell_s$	$Sell_s$
	Model 1	Model 2		Model 3	Model 4
$valence_{s-1}$	.237*	.238*	$fear_s$	4.995***	4.861***
$money_{s-1}$	7.29e-06	4.95e-06	$money_{s-1}$	3.42e-06	3.87e-06
$units_{s-1}$	-.021**	-.015	$units_{s-1}$	.048***	.044***
$P\ level_{s-1}$	-.00007	-.00008	$P\ level_{s-1}$	.00012	-.00012
Buy_{s-1}	.355***		$Sell_{s-1}$	.363***	
	Prob>chi2 =0.000	Prob>chi2 =0.0586		Prob>chi2 =0.000	Prob>chi = 0.000
	9770 obs	9770 obs		9970 obs	9970 obs
	49 groups	49 groups		50 groups	50 groups

Table 4: Individual behaviour: trading activity depending on past emotions for different types of traders. ***(Poisson count regression with subject fixed effects)***

Buy_s	Fundamental Value Trader	Momentum Trader	Rational Speculator Trader
$Valence_{s-1}$	.280	.521**	-.025
$Money_{s-1}$	.00003	-.00004	-.00007**
$Units_{s-1}$	.015	-.119***	-.068***
Price $level_{s-1}$	-.0004*	.0007***	3.15e-06
Buy_{s-1}	.435***	.141*	.370***
	Obs: 3762 Groups: 19 Prob>F =.0000	Obs: 3396 Groups: 17 Prob>F =.0000	Obs: 2612 Groups: 13 Prob>F =.0000

$Sell_s$	Fundamental Value Trader	Momentum Trader	Rational Speculator Trader
$Fear_s$	4.601	4.641**	9.492
$Money_{s-1}$	-.00005**	-.00006*	.00001***
$Units_{s-1}$	.069***	.027	.077***
Price $level_{s-1}$	.0003	-.0006**	.0001
$Sell_{s-1}$	.354***	.294***	.458***
	Obs: 3963 Groups: 20 Prob>F =.0000	Obs: 3396 Groups: 17 Prob>F =.0000	Obs: 2612 Groups: 13 Prob>F =.0000

Table 5: Individual behaviour: Number of bids and asks as a function of neutrality and market variables *(logit model with subject fixed effects)*

	$bids_s$	$asks_s$	$Bids\&asks_s$
$neutrality_{s-1}$	-.247**	-.031	-.126*
$money_{s-1}$	-.00008***	.00005***	9.81e-06
$units_{s-1}$	-.058***	.054***	.020***
$price\ level_{s-1}$	-.0002	.0001*	-.0001
$bids_{s-1}$	.128***		
$asks_{s-1}$		.097***	
$Bids\&asks_{s-1}$			.103***
	Obs: 9770	Obs: 9971	Obs: 9971
	Groups: 49	Groups: 50	Groups: 50
	Prob>F =.000	Prob>F =.000	Prob>F =.000

Table 6: Individual behaviour: Emotions depending on overall financial position ***(subject fixed effects)***

	Valence_{s}	Valence_{s}
money_{s-1}	2.51e-06*	4.01e-06**
units_{s-1}	.0013*	.0022***
P level_{s-1}	-.000044***	-.000087***
valence_{s-1}	.480***	
const.	-.028**	-.046***
	Obs: 9927 Groups: 50 Prob>F =.000	Obs: 9970 Groups: 50 Prob>F =.000

Table 7: Individual behaviour: Emotions depending on recent trading activity *(subject fixed effects)*

	Valence $_s$ Model 1	Valence $_s$ Model 2	Valence $_s$ Model 3	Valence $_s$ Model 3	Valence $_s$ Model 4
const	-.031***	-.016***	-.005*	-.006**	-.003
buy $_{s-1}$	.001	.001	.002		
sell $_{s-1}$	.004	.003	.002		
valence $_{s-1}$		.483***	.472***	.474***	.478***
Profit buy $_{s-1}$			.00002**	.00001	
Profit sell $_{s-1}$			-.00001*		6.07e-07
Price level $_{s-1}$				-.00003**	-.00005***
	Obs: 9970 Groups: 50 Prob>F =.6734 R2=0.0001	Obs: 9927 Groups: 50 Prob>F =.000 R2=0.355	Obs: 8990 Groups: 49 Prob>F =.000 R2=0.351	Obs: 9328 Groups: 49 Prob>F =.000 R2=0.353	Obs: 9444 Groups: 50 Prob>F =.000 R2=0.353

	Fear $_s$ Model 1	Fear $_s$ Model 2	Fear $_s$ Model 3	Fear $_s$ Model 3	Fear $_s$ Model 4
const	.0009***	.0005***	.0009***	.0005***	.001***
buy $_{s-1}$	.0007***	.0004***	.0003***		
sell $_{s-1}$	.00005	-.0001	.0001		
Fear $_{s-1}$		.454***	.101***	.456***	.102***
Profit buy $_{s-1}$			5.47e-07	4.33e-07	
Profit sell $_{s-1}$			-2.21e-07		-2.95e-07
Price level $_{s-1}$				7.30e-07	-3.19e-07
	Obs: 9970 Groups: 50 Prob>F =.0003 R2=0.0009	Obs: 9927 Groups: 50 Prob>F =.000 R2=0.250	Obs: 8990 Groups: 49 Prob>F =.000 R2=0.017	Obs: 9328 Groups: 49 Prob>F =.000 R2=0.251	Obs: 9444 Groups: 50 Prob>F =.000 R2=0.018

Table 8: The correlation between price level and emotions

	Fear	Valence	Happiness	Anger	Surprise	Disgust	Sadness	Neutrality
Price Level	.390***	-.090***	-.007	-.070***	-.267***	-.033***	.074***	-.363***

Table 9: The correlation between loss aversion measure and emotional state

	Fear	Valence	Happiness	Anger	Surprise	Disgust	Sadness	Neutrality
Loss aversion	.342***	-.301**	-.045	-.068	-.085	.209	.109	-.198
	(.018)	(.025)	(.759)	(.649)	(.569)	(.157)	(.463)	(.180)

Number of observations: 55

Figure 1: Facereader Output

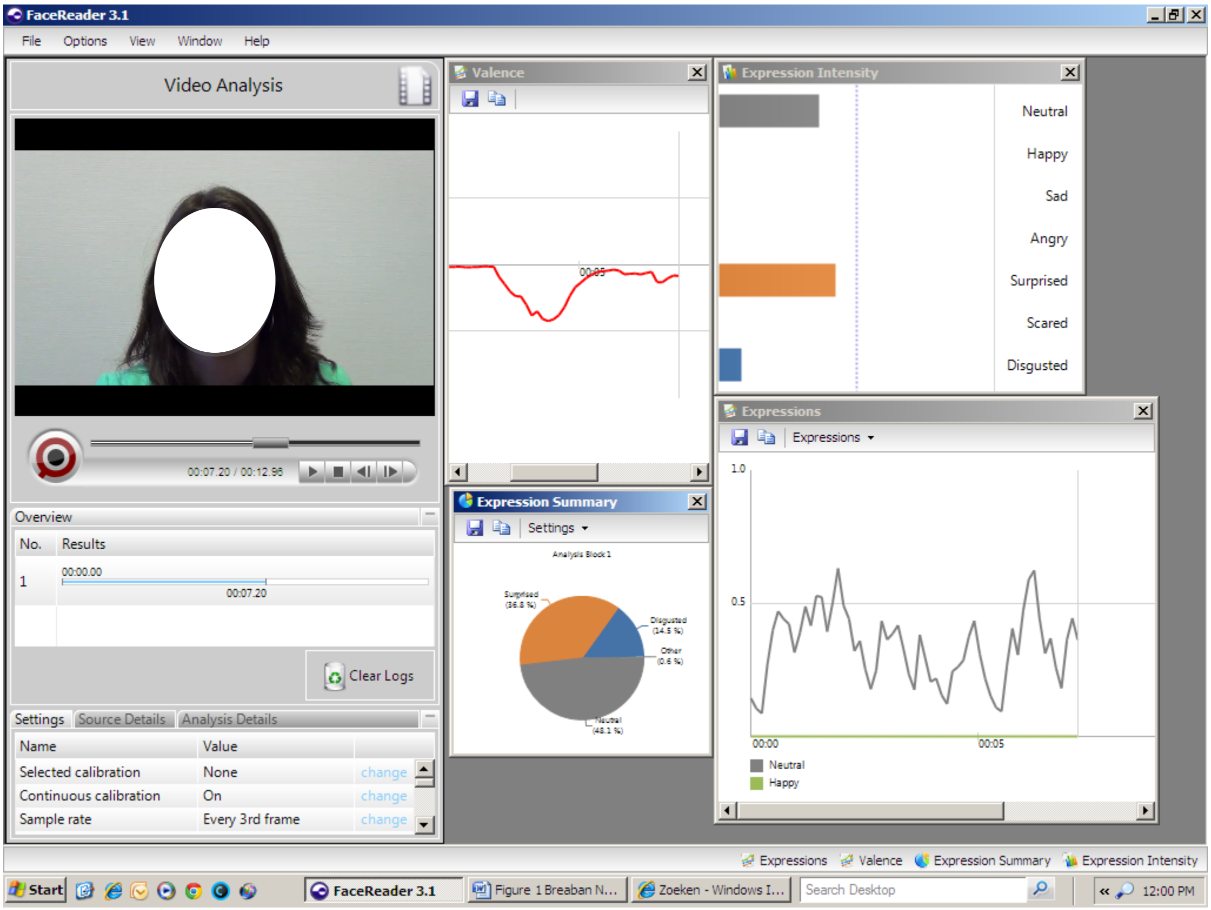


Figure 2: Average Transaction Price, All Periods, All Markets

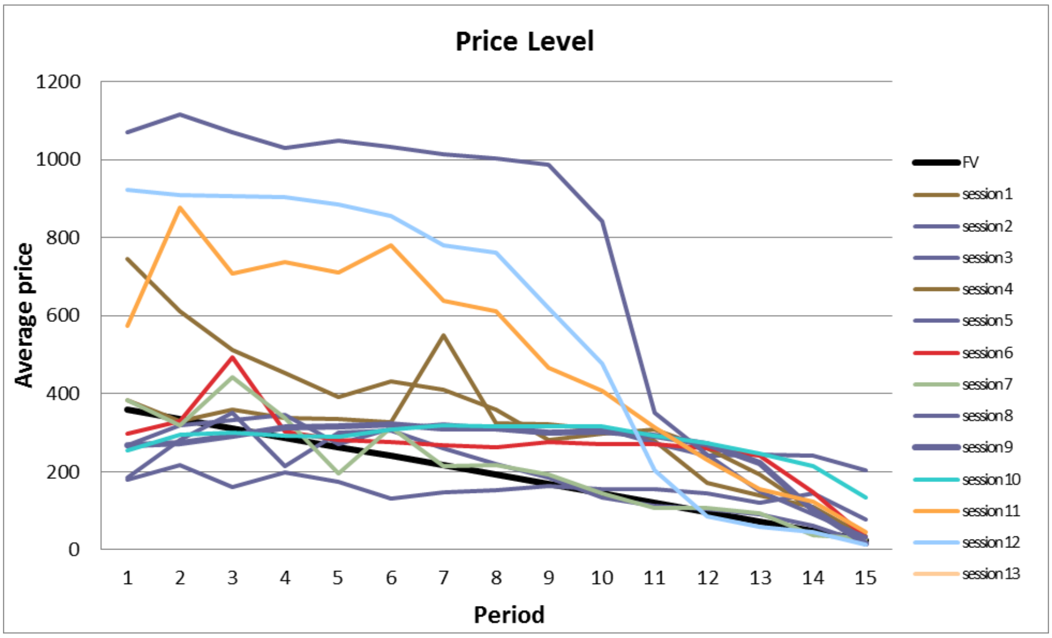


Figure 3: Emotional Valence Prior to Market Open and Price Level

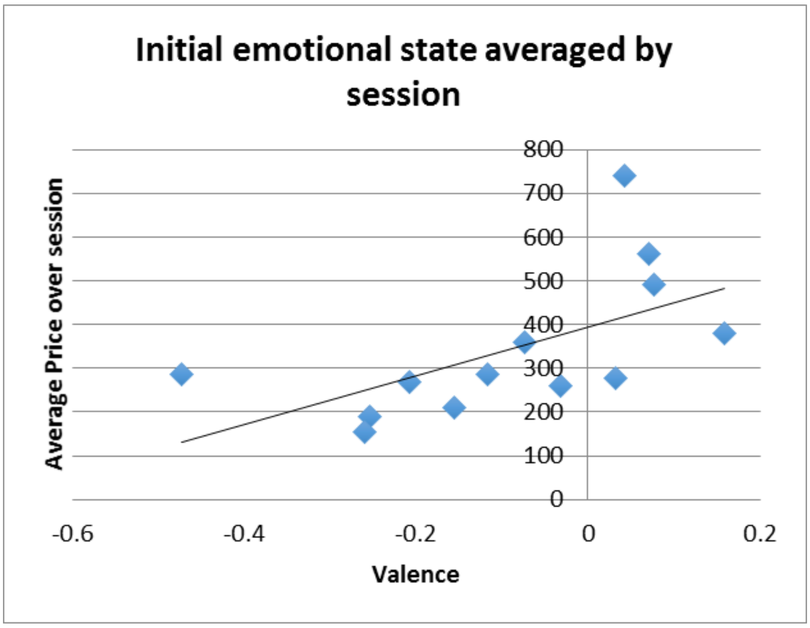


Figure 4: Fear Prior to Market Open and Price Level

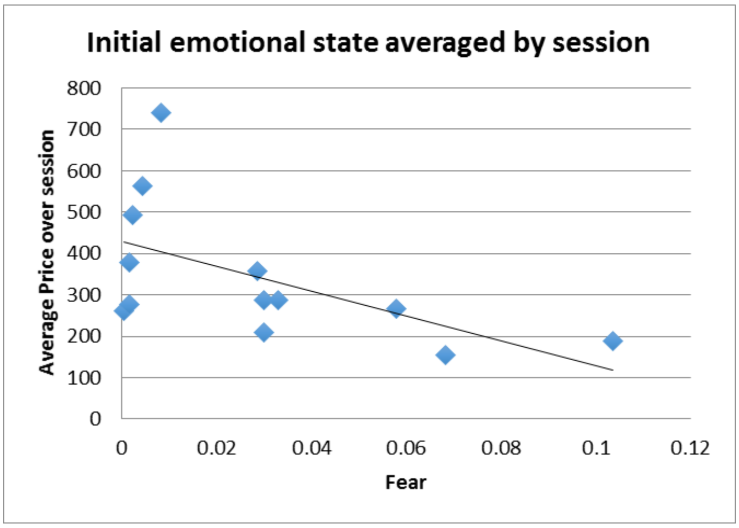


Figure 5: Emotional dynamics in a crash

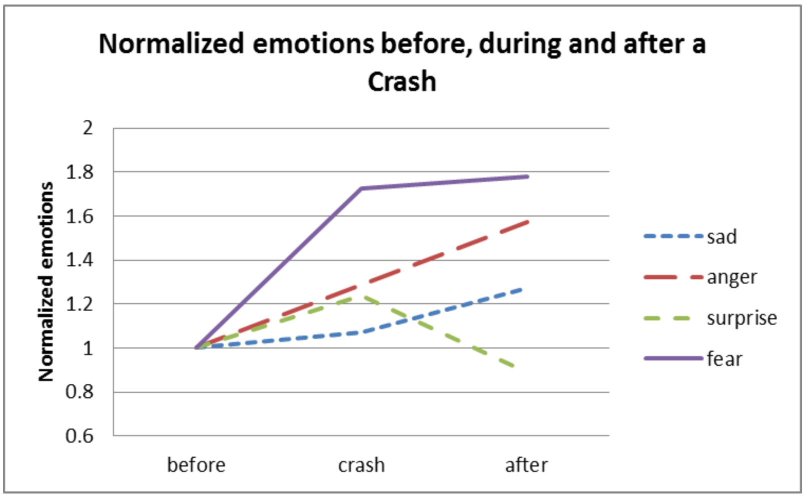
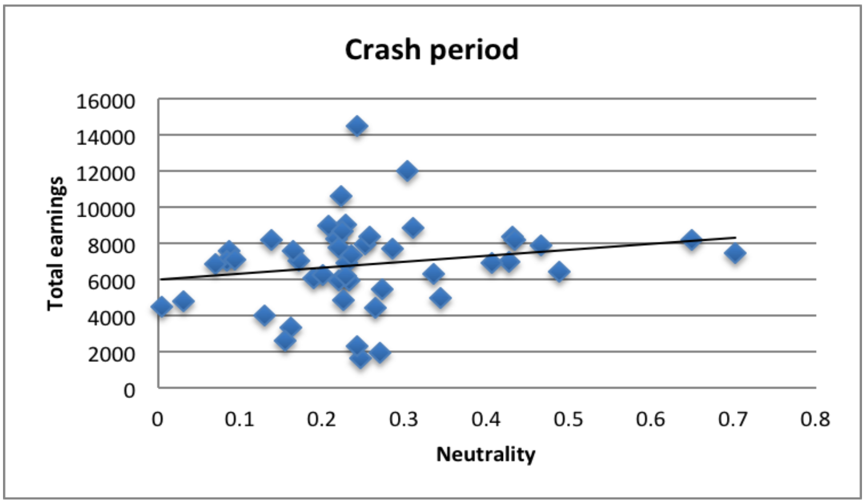


Figure 6: Relationship between Neutrality and Earnings, Crash Period



APPENDIX I: Instructions for the Loss Aversion Measurement Task

Welcome to this experiment. The instructions are simple and if you follow them carefully and make good decisions, you might earn a considerable amount of money, which will be paid to you by bank transfer at the end of the experiment.

The session will be divided in two parts and you will have the opportunity to earn money in both of them.

Part I

In the first part of the experiment six bets will be presented to you. Each bet gives you a 50-50 chance of winning some money or losing some money.

For each bet, you must decide if you want to play it or not, although only one randomly chosen decision will count toward your earnings.

After all participants have made their decisions for each of the six bets, the experimenter will roll a six-sided die. The outcome of the roll will determine the one single bet that will count to determine your earnings. If the die reads 1, you will be paid for your decision in the first lottery. If the die reads 2, you will be paid for your decision in the second lottery, and so on. Exactly one of the six bets will count.

After the die is rolled, if you decided not to play the bet chosen by the die roll, your earnings will be 0 euros for this part of the experiment.

If you decided to play that bet chosen by the die roll, there will be a 50-50 chance for you to win or lose the amount of money indicated in the bet. Then, the experimenter will toss a coin for each participant. If the coin comes up heads you lose and if the coin comes up tails you win the amount of money specified in the lottery.

Lottery (50-50 chance)	**Accept to play?**	
Lose 0.5€ or win 4.5€	○ Yes	○ No
Lose 1.5€ or win 4.5€	○ Yes	○ No
Lose 2.5€ or win 4.5€	○ Yes	○ No
Lose 3.5€ or win 4.5€	○ Yes	○ No
Lose 4.5€ or win 4.5€	○ Yes	○ No
Lose 5.5€ or win 4.5€	○ Yes	○ No

APPENDIX II: Instructions for the Asset Market

1. General Instructions

The second part of the experiment consists of a sequence of trading Periods in which you will have the opportunity to buy and sell in a market. The currency used in the market is ECU. All trading will be done in terms of ECU. The final payment to you at the end of the experiment will be in euros. The conversion rate is: **500 ECU to 1 euro.**

2. How to use the computerized market

In the top right hand corner of the screen you see how much time is left in the current trading Period. The goods that can be bought and sold in the market are called Shares. On the left side of your screen you see the number of Shares you currently have and the amount of Money you have available to buy Shares.

If you would like to offer to sell a share, use the text area entitled “Enter offer to sell” in the first column. In that text area you can enter the price at which you are offering to sell a share, and then select “Submit Offer To Sell”. Please do so now. Type in a number in the appropriate space, and then click on the field labeled “Submit Offer To Sell”. You will notice that nine numbers, one submitted by each participant, now appear in the second column from the left, entitled “Offers To Sell”. Your offer is listed in blue. Submitting a second offer will replace your previous offer.

The lowest offer-to-sell price will always be on the bottom of that list. You can select an offer by clicking on it. It will then be highlighted. If you select “Buy”, the button at the bottom of this column, you will buy one share for the currently selected sell price. Please purchase a share now by selecting an offer and clicking the “Buy” button. Since each of you had offered to sell a share and attempted to buy a share, if all were successful, you all have the same number of shares you started out with. This is because you bought one share and sold one share. Please note that if you have an offer selected and the offer gets changed, it will become deselected if the offer became worse for you. If the offer gets better, it will remain selected.

When you buy a share, your Money decreases by the price of the purchase. When you sell a share your Money increases by the price of the sale. You may make an offer to buy a unit by selecting “Submit offer to buy.” Please do so now. Type a number in the text area “Enter offer to buy”, then press the red button labeled “Submit Offer To Buy”. You can replace your offer-to-buy by submitting a new offer. You can accept any of the offers-to-buy by selecting the offer and then clicking on the “Sell” button. Please do so now.

In the middle column, labeled "Transaction Prices", you can see the prices at which Shares have been bought and sold in this period. You will now have about 5 minutes to buy and sell shares. This is a practice period. Your actions in the practice period do not count toward your earnings and do not influence your position later in the experiment. The only goal of the practice period is to master the use of the interface. Please be sure that you have successfully submitted offers to buy and offers to sell. Also be sure that you have accepted buy and sell offers. If you have any questions, please raise your hand and the experimenter will come by and assist you.

3. Specific Instructions for this experiment

The experiment will consist of 15 trading periods. In each period, there will be a market open for 2 minutes, in which you may buy and sell shares. Shares are assets with a life of 15 periods, and your inventory of shares carries over from one trading period to the next. You may receive dividends for each share in your inventory at the end of each of the 15 trading periods.

At the end of each trading period, including period 15, the computer will randomly determine the dividend value for all shares in that period. Each period, each share you hold at the end of the period:

earns you a dividend of 0 ECU with a ¼ chance

earns you a dividend of 8 ECU with a ¼ chance

earns you a dividend of 28 ECU with a ¼ chance

earns you a dividend of 60 ECU with a ¼ chance

Each of the four dividend values is equally likely, thus the average dividend in each period is 24. Dividends are added to your cash balance automatically.

After the dividend is paid at the end of period 15, there will be no further earnings possible from shares.

4. Average Holding Value Table

You can use your AVERAGE HOLDING VALUE TABLE to help you make decisions. There are 5 columns in the table. The first column, labeled Ending Period, indicates the last trading period of the experiment. The second column, labeled Current Period, indicates the period during which the average holding value is being calculated. The third column gives the number of holding periods from the period in the second column until the end of the experiment. The fourth column, labeled Average Dividend per Period, gives the average amount that the dividend will be in each period for each unit held in your inventory. The fifth column, labeled Average Holding Value Per Unit of Inventory, gives the average value for each unit held in your inventory from now until the end of the experiment. That is, for each share you hold for the remainder of the experiment, you will earn on average the amount listed in column 5.

Suppose for example that there are 7 periods remaining. Since the dividend on a Share has a 25% chance of being 0, a 25% chance of being 8, a 25% chance of being 28 and a 25% chance of being 60 in any period, the dividend is on average 24 per period for each Share. If you hold a Share for the remaining 7 periods, the total dividend for the Share over the 7 periods is on average 7*24 = 168. Therefore, the total value of holding a Share over the 7 periods is on average 168

AVERAGE HOLDING VALUE TABLE

Ending Period	Curent Period	Number of Remaining Periods	Average Dividend per Period	Average Holding Value per Unit of Inventory
15	1	15	24	15x24=360
15	2	14	24	14x24=336
15	3	13	24	13x24=312
15	4	12	24	12x24=288
15	5	11	24	11x24=264
15	6	10	24	10x24=240
15	7	9	24	9x24=216
15	8	8	24	8x24=192
15	9	7	24	7x24=168
15	10	6	24	6x24=144
15	11	5	24	5x24=120
15	12	4	24	4x24=96
15	13	3	24	3x24=72
15	14	2	24	2x24=48
15	15	1	24	1x24=24

5. Your Earnings

Your earnings for this part of the experiment will equal the amount of cash that you have at the end of period 15, after the last dividend has been paid. The amount of cash you will have is equal to:

The cash (called “Money” on your screen) you have at the beginning of the experiment

+ dividends you receive

+ money received from sales of shares

- money spent on purchases of shares