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Emotions, Beliefs and Illusionary finance

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To my parents Liliana, Carlos,
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CHAPTER 1

Introduction

The purpose of my thesis is to integrate behavioral finance with market microstructure and financial decision making. Specifically, I focus on two issues concerning the integration of psycho-physiological mechanisms and the informational content of prices in financial markets: firstly, the role of emotions in financial decision making and how as an adaptive mechanism, they show to be more suitable for survival than pure rationality (in an economic sense); and secondly, the empirical and theoretical testing of how cognitive illusions and polysemy affect the informational content of prices.

Emotions and cognitive illusions are psychological complexities which have been extended beyond the judgement and decision making field. Emotions are certainly important to understand how markets work and how traders will react either to changes, or under the finding of an 'unawareness' state that can change their perception of the current state of world. While emotions represent the benevolent side of financial decision making, illusions represent the conscious or unconscious possibility of having a biased belief driven by fast thinking and the use of heuristics; or the possibility of someone taking advantage of human failure in objective thinking in order to maximize his/her own profit

1.1 The role of emotions in financial decision making

Traditional financial theory is built upon the assumption that investors make rational decisions all the time with the ultimate objective of maximizing their utility within an environment surrounded by risk and uncertainty. The standard economic model of decision making assumes that the current emotional state has no impact on an individual decision. Yet there is a large body of psychological literature that shows that the current emotional state, in particular positive affect, has a significant effect on decision making, problem solving, and behavior.

Some research has pointed out the almost impossibility of making decisions based on pure logic. For example, Barber and Odean (2001) find that an investor using the Internet to gather information to make an investment decision has access to over three billion pieces of information. Damasio's research suggests how emotions help us focus on certain information. He argues that we have emotional responses, or "somatic markers", to certain outcomes or actions and this determines the focus of our attention.

There is also considerable support for economic behavior being affected by emotions. Bechara et al (1997) find that strategy and performance in a risky card game was influenced by whether or not the participants could experience emotions. Participants who could not experience emotions were more likely to follow a high risk strategy (where they could either win a large amount or lose a large amount), while participants with a normal ability to experience emotions were more likely to follow a risk averse strategy (where they could consistently win small amounts). The authors argue that the participants who could not experience emotions did not experience the emotional deterrent attached to the possibility of losing a large amount. In other research showing a role for emotions in economic decision-making, Luce, Payne and Bettman (1999) find that the consumers desire to avoid negative emotions has an effect on their purchase selection.

Loewenstein, ODonoghue and Rabin (2002), and Laibson (2000) outline many instances of the influence of emotions on economic behavior among others on advertising and on consumer expenditure.

Evidence of emotions affecting financial decision-making can be seen from purchasing patterns in insurance, where people are more likely to spend money on insurance against emotionally vivid events, even if these events are not very probable (Johnson et al., 1993).

Loewenstein (2000 p. 426) argues that the emotions and feelings experienced at the time of making a decision "often propel behavior in different directions from those dictated by a weighing of the long-term costs and benefits of disparate actions". Equity pricing involves the weighing of long-term benefits (the right to a share in the future net cash flows due to an equity) and costs (the riskiness of the future cash flows), so it seems reasonable to speculate that the emotions and feelings of investors influence their pricing of equities. Under the label of neurofinace, two recent areas of stock market research have addressed the impact of feelings on investor decision-making: The first area covers mood misattribution. This area investigates the impact of factors, such as affect and social factors, on equity pricing. This area builds on research from psychology which argues that people's decisions are guided, in part, by their feelings. While this is generally beneficial for efficient decision-making, people sometimes allow feelings induced by transient factors, such as their personal mood or external circumstances such as weather, to influence unrelated decisions. This phenomenon is labeled as "mood misattribution". In this way, mood fluctuations (which are widely experienced in complex decisions involving risk and uncertainty) may partially influence equity investment decisions. For example, compared to the judgments of people in a neutral mood, people in a good mood are argued to make more optimistic judgments about equities, and people in a bad mood are argued to make more pessimistic judgements.

The second area of research looks at the impact of image on investor's decision-making. The argument here is that the image of a stock, induces emotions in investors that partially drive their investment behaviour. This area of research can be contrasted with the first area of research, in that it is concerned with emotion arising out of the investment decision-making process, whereas the environmental factor research is concerned with the impact of emotions arising out of events unrelated to the investment decision-making process.

The traditional perspective of how people make decisions involving conditions of risk and uncertainty assumes what Loewenstein et al (2001) describe as a "consequentialist perspective". In this traditional model, the decision-maker is assumed to quantitatively weigh the risks and benefits of all possible outcomes, and choose the outcome with the best risk-benefit trade-off. This perspective can be seen in the traditional finance theories of Markowitz portfolio theory (Markowitz, 1952) and the Capital Asset Pricing Model (e.g. Sharpe, 1964).

The traditional consequentialist perspective is argued to be unrealistic as it takes no account of the influence of feelings on decision-making. There is ample evidence that feelings do significantly influence decision-making, especially when the decision involves conditions of risk and/or uncertainty (e.g. Zajonc, 1980; Schwarz, 1990; Forgas, 1995; Isen, 2000; Loewenstein et al., 2001). An advance on the traditional perspective has been to include the impact of anticipated emotions on decision-making. Anticipated emotions are emotions that are expected to be experienced by the decision-maker given a certain outcome. For example, it might be assumed that the decision-maker is influenced by the effect of emotions such as regret and disappointment if they experience a negative outcome (this can be seen in the model of regret developed by Loomes and Sugden, 1982). This perspective has been applied in finance; for example, the "myopic loss aversion" theory of Benartzi and Thaler (1995) utilises the implication of the emotional reaction of investors' losses on their investments to explain the equity risk premium puzzle identified by Mehra and Prescott (1985). While the inclusion of anticipated emotions is an advance over the traditional consequentialist perspective, the perspective does not incorporate the significant influence of emotions experienced at the time of making a decision on the decision-maker. Thus, for example, it does not incorporate the finding that people in good moods at the time of making a decision make different decisions from people in negative moods (e.g. Schwarz, 1990).

The "risk-as-feelings" model was developed by Loewenstein et al (2001) primarily to incorporate the fact that the emotions people experience at the time of making a decision influence their eventual decision. The model is based on a number of premises, each of which is well-supported. The combined effect of the premises of the risk-as-feelings model is to show that every aspect of the decision-making process is influenced by the feelings of the decision-maker.

The four premises of the risk-as-feelings model are:

1. Cognitive evaluations have emotional reactions. This argument is well established by psychologists. In a review of psychologists research on emotions and feelings, Zajonc (1980) summarises that emotions are "considered by most contemporary theories to be postcognitive, that is, to occur only after considerable cognitive operations have been accomplished" (p. 151).

2. Emotions inform about cognitive evaluations. The idea that emotions inform about cognitive evaluations is also well established by researchers in psychology and decision-making. It can be seen from the body of research showing that people in positive moods tend to make optimistic judgements, while people in negative moods tend to make pessimistic judgements (e.g. Isen et al., 1978; Bower, 1981; Johnson and Tversky, 1983; Bower, 1991). For example, Isen et al (1978) found that inducing good mood in people by giving them a gift, led to more favourable reviews of a shopping experience.

3. Feelings can arise without cognitive antecedents. The idea that feelings can arise without cognitive antecedents is made most forcefully by Zajonc (1980), LeDoux (1994; 1996), and

Panksepp (1982; 1998). While this argument is slightly controversial among psychologists, the arguments for and against feelings arising without cognitive antecedents are not of great relevance to the study of whether investor decision-making is influenced by feelings.

4. Feeling can affect behavior. Damasio (1994) showed that emotions play a vital role in decision-making by studying people who had an impaired ability to experience emotion. People with impaired ability to experience emotions had difficulty in making decisions and tended to make suboptimal decisions.

The Affect Infusion Model (AIM) of Forgas (1995) addresses the idea that people rely on their feelings. Forgas states that feelings affect decision-making depending on how risky, uncertain and abstract the decision is. He argues that there are Low Affect Infusion Strategies (LAIS) and High Affect Infusion Strategies (HAIS). LAIS are typically used in decisions that require little generative, constructive processing (p. 40). LAIS would be used for decisions that people are familiar with and that have a low complexity. HAIS involve the use of feelings as a major input into the decision-making process. Typically, HAIS are employed when the decision is highly complex and the decision-maker is boundedly rational. Thus, we would expect that the more complex the decision (e.g. equity investment decisions), the greater the influence of feelings on the decision.

Researchers that investigate the influence of decision-makers bounded rationality on economic behavior have been particularly keen to incorporate emotions into their models (see Simon, 1967, 1983; Etzioni, 1988; Kaufman, 1999; Hanoch, 2002). For example, Simon (1983) argued that, "in order to have a complete theory of human rationality, we have to understand the role emotion plays in it" (p. 20). The area where feelings are potentially of greatest importance is in making "satisficing" decisions. Satisficing behavior is defined by Simon (1987b) as "faced with a choice situation where it is impossible to optimize, or where the computational cost of doing so seems burdensome, the decision-maker may look for a satisfactory, rather than an optimal, alternative" (p. 243). Conlisk (1996) argues that making a decision is costly in terms of time and resources, and that satisficing is a means of avoiding the deliberation costs associated with rational decision-making. In fact, optimal decision-making is possibly suboptimal as the cost of making an optimal decision might be more than the loss incurred from making a satisficing decision. This drives Knight (1921) to say "it is evident that the rational thing to do is to be irrational, where deliberation and estimation cost more than they are worth" (p. 67). Emotional decision-making is a means of avoiding the deliberation cost associated with optimal decision-making. Allowing emotions to partially drive the satisficing decision involves less deliberation cost, and can be quite efficient according to Lo and Repin (2001) who argue that this type of "intuitive" decision-making allows a "large number of cues [to be] processed simultaneously" (p. 13). In contrast to this point of view of emotions aiding efficient decision- making, however, Kaufman (1999) argues that extreme states of emotion (extremely high emotional arousal or extremely low arousal) lead to increased bounded rationality as emotions cloud the decision makers judgements.

Lo and Repin (2001) took a novel approach to investigate whether feelings play a role in investor decision-making. Using a sample of 10 professional traders of financial derivatives, they attach biofeedback equipment to each trader in order to collect information on the physiological characteristics associated with emotional reactions. They find that traders have heightened emotional arousal around important events such as increased volatility of prices. The authors argue that the ability to make quick decisions by reference to their emotions is necessary for the rapid decision-making required of successful derivative traders. The authors do not investigate whether heightened emotional arousal is associated with negative or positive performance by traders.

Mehra and Sah (2002) also provides theoretical support for feelings influencing equity prices. Mehra and Sah argue that the feelings of investors will have an effect on equity prices if:

1. Investors "subjective parameters" (such as their level of risk aversion and their judgement of the appropriate discount factor) fluctuate over time due to fluctuations in mood;

2. The effects of these fluctuations in mood on investor's subjective parameters are widely and uniformly experienced; and

3. Investors do not realise their decisions are influenced by fluctuations in their moods

Based on these three premises, Mehra and Sah argue that fluctuations in investor mood will be linked to fluctuations in equity prices.

The mood-as-information hypothesis argues that our moods inform our decisions; in effect, when we are making a decision we ask ourselves "How do I feel about it?" and this guides our eventual decision (Schwarz and Clore, 1988; Schwarz, 1990; Clore and Parrott, 1991). The general impact of mood is summarised by Schwarz (1990) as: Negative affective states, which inform the organism that its current situation is problematic, triggering the use of effortful, detail-oriented, analytical processing, whereas positive affective states, triggering the use of less effortful heuristic strategies. (p. 527)

Moods tend to inform decisions even when the cause of the mood is unrelated to the decision being made. For example, in Schwarz and Clore (1983), transient fluctuations in the weather had a large influence on peoples assessment of their life satisfaction. Yet, objectively it should only have had a very minor, perhaps even no influence on the rating of life satisfaction. This phenomenon is labelled misattribution. Johnson and Tversky (1983) reported on how misattribution can affect risk assessments. In one experiment in this paper, some subjects were asked to read negative news stories in order to induce depression. These subjects were then asked to rate the riskiness of 18 possible causes of death. The subjects rated the riskiness of death higher than subjects who did not read the negative news story. In another study in the same paper, the authors found that asking subjects to read a positive news story resulted in them rating riskiness of the various causes of death lower than subjects who did not read a positive news' story. This relationship held even when the information in the news story was unrelated to the cause of death being rated.

Shiller (1984; 2000) argues that the fashions and fads that affect people in their everyday lives, also affect equity pricing. Investors spend a substantial part of their leisure time discussing investments, reading about investments, or gossiping about others successes or failures in investing. It is thus plausible that investor behaviour (and hence prices of speculative assets) would be influenced by social movements. (1984, p. 457).

In support of Shiller, Hong, Kubik and Stein (2001) find that households who interact with other households are more likely to invest in the stock market than non-social households. It is, therefore, possible to hypothesise that widely experienced fluctuations in social moods influence equity returns, with positive social feelings resulting in optimistic/higher equity pricing and negative social feelings resulting in pessimistic/lower equity pricing.

1.2 Illusions and the informational content of prices

The term **illusion** comes from the Latin verb *illudere* which means "to mock at, to make fun of, to ridicule"[1]. An illusion denotes the action of deceiving, the state or fact of being intellectually deceived or misled or something that deceives or misleads intellectually, the perception of something objectively existing in such a way as to cause misinterpretation of its actual nature, or a misleading image presented to the vision.[2]

A more formal definition is given in Pohl (2004a), p. 2-3, according to which an illusion can be defined through the following essential properties:

(i) An illusion results in a perception, judgement or memory that *deviates from reality*,

(ii) The deviation is *reliable and systematic*[3],

(iii) An illusion appears *involuntarily*[4],

(iv) It is *hard if not impossible to avoid*.

Gheorghiu, Molz, and Pohl (2004a) further conceptualize the notion of illusion, focussing on four specific domains:

1. The *illusive situation* - where we can distinguish among three cases:
   - ◇ Perceiving illusion as reality - e.g. different things (such as dependent and independent, random and deterministic events, etc.) are pooled together to the same category in spite of their distinct features, equivalent things are subjectively interpreted to be different, or quantitative differences are considered to be valid indicators for qualitative attributes;
   - ◇ Perceiving reality as illusion - as a result of the reinterpretation of real aspects,
   - ◇ Perceiving reality as non-reality - through the omission of important elements which then appear to be non-existent.
2. The *readiness to be illusioned (illusionability)* - is determined by individual differences (such as intelligence, memory capacity, and acquiescence) and relies on:
   - ◇ ambiguity - that results from uncertainty, complexity, lack of accessibility or transparency, etc.,

[1]Latin-English dictionary, http://humanum.arts.cuhk.edu.hk/Lexis/Latin/.
[2]Merriam-Webster Online dictionary, http://www.m-w.com/dictionary.
[3]So that its direction can be predicted.
[4]So that the illusioned persons are firmly convinced that judgments and decisions are correct.

- ◇ certain cognitive mechanisms - such as striving for economy, ascribing meaning, acting in anticipation of expected results, relying on imaginary capacities, pretending, or acting self-centered.

3. *Illusive techniques* - sophistication by external factor or agents can induce cognitive propensities connected to possible illusions.

4. The *functions of illusions with respect to thinking, judgment, and memory.*

The human mind displays a voracious appetite when it begins to seek out and assimilating new information - even information with which it does not necessary agree. Financial markets are not different. They display an insatiable appetite for new thoughts and ideas. In short, financial markets are huge information consumers.

Financial markets are an informational imperfect world where investors actively search for the truth about informational determinants of a particular asset price. A considerable portion of time, effort and resources is devoted to the production and gathering of information itself. Active investment financial players collectively employ thousands of analysts, economists, strategists, quants and market technicians, whose primary goal is to garner all the important information "edge" - an "edge" that they believe is not yet reflected in prices.

Research from evolutionary finance (Hens et al. (2002); Hens et al (2005), Farmer (2002) and Dowling(2005)) has shown that investors appear to interpret information in a way that is highly analogous to the biological process of molecular attraction. Investors encode, associate, and assimilate new information. However, different investors have different interpretation capabilities and cannot possibly fully project the consequences of information. Thus, they are willing to pay a price to an analyst "with superior ability" who can assist them in forming a better investment judgment.

In their search of the important information "edge", investors might be deceived or misled by another market participant who is trying to ensure his survival relying on the inability of the first one to clearly *understand* the complexity of the information "edge" itself.

The definition we adopt for illusions in financial markets is the perception of something objectively existing and created intentionally by someone in such a way that its actual nature is misinterpreted. We call the illusionist or illusionary trader the one who creates the illusion. An illusionary trader creates an illusion by sending polysemous signals to the market and taking advantages of the other traders psychological biases and time pressure in order to obtain a positive return. The psychological notions that introduce illusionary trading in stock markets are bounded rationality, intuition and reasoning, framing effects, attribute substitution, and prospect theory.

In order to understand the foundations of illusions in financial markets we need to understand that as any other economic agent, traders in a stock market face cognitive processes like those presented in Kahneman and Frederick (2002). Furthermore, they are confronted by time pressure and polysemous signals when making their decisions. They must decide in a very short period of time which information is important and incorporate it in their information set in order to form their expectations. According to Kahneman and Frederick(2002), cognitive processes can be divided into two families: intuition and reasoning.[5] Intuition is a process that is spontaneous, effortless, and fast. Reasoning is deliberate, rule-governed. It requires considerable effort, and is slow. Usually, the relevant characteristic to differentiate between both systems is the effort and the time. A trader is subject to these cognitive processes (intuition and reasoning) when he takes his decisions.

Although intuition is present in most of our judgements and choices, it is normally monitored by reasoning (system 2). However, this monitoring is lax; many judgements and choices are expressed even if some of them are erroneous. Intuition (system 1) can deal with stored concepts and precepts and can be evoked by language. Intuition comes to mind very fast in the form of percepts. The ease with which mental concepts come to mind is known as *accessibility*. Some attributes are more accessible than others. Attributes that are routinely and automatically produced by the perceptual system [6], or by intuition have been called *natural assessments*, such as similarity, causal propensity, surprisingness, affective valence, and mood. Some determinants of accessibility are probably genetic, but others are developed through experience. The acquisition of skills gradually increases the accessibility of useful responses and of productive ways to organize information. Skills are acquired by long exercises, but once they are obtained they come to the mind rapidly and effortlessly. Thus, the cognitive system has two ways of adjusting to changes: a short-term process that is flexible and effortless, and a long-term process of skill acquisition that eventually produces highly effective responses at low cost. Some of the most highly skilled cognitive activities are intuitive, but the intuition is prone to systematic biases and errors that are sometimes not corrected at all and are rarely corrected perfectly.

An important factor that influences the agents' judgements and decisions given by their intuitions is the framing effect. The framing effect refers to problems that can be equivalently described in many different ways leading to different choices simply by altering the relative salience of different aspects of them. The different representations of the outcomes highlight some features of the situation and mask others. Agents (i. e. traders) can react differently depending on the highlighted and masked features. Furthermore, Tversky and Kahneman (1974) argue that "people rely on a limited number of heuristic principles which reduce the complex tasks of assessing probabilities and predicting values to simple judgements operations. [7] In general, these heuristics are quite useful, but sometimes they lead to severe and systematic errors."

Due to time pressure and time available for deliberation, people's ability to avoid errors of intuitive judgement is impaired (Finucane, Alhakami, Slovic, and Johnson (2000)). This is true for traders who need to take decisions on spot. For example, their ability is impaired by concurrent involvement in several different cognitive tasks if the agent is mentally occupied

[5] According to the labels given by Stanovich and West (2000), intuition is known as system 1 and reasoning as system 2.

[6] Perception is the awareness that comes from the stimuli of the physical world, the sensation of it and our experience in interpreting it. Perception is the basic way of knowing reality. But although perception seems accurate , it is often subject to weaknesses and limits (Cobb (1999)).

[7] This is related to the concept of attribute substitution from Kahneman and Frederick (2002): "a judgement is said to be mediated by a heuristic when the individual assesses a specified target attribute of a judgement object by substituting another property of that object (the heuristic attribute) which comes more readily to mind." This means that agents confronted with a difficult question often answer an easier one instead, usually without being aware of the substitution.

by a demanding mental activity (Gilbert(1989, 1991, 2002)); by performing the task in the evening for "morning people" and in the morning for "evening people" (Bodenhausen (1990)); and surprisingly, by being in a good mood (Isen, Nygren, and Ashby (1988)). Conversely, the facility of reasoning is positively correlated with exposure to statistical thinking (Nisbett, Krantz, et al. (1983); Agnoali and Krantz (1989); and Agnoli (1991)) and with intelligence (Stanovich and West(2000)), a trait that psychologists have labeled "need for cognition" (which is roughly whether people find thinking pleasurable) (Shafir and Leboeuf(2002)).

In summary, agents do not make fully-rational decisions, at least in the economic sense. Instead, their decisions are based on "bounded rationality".[8] Kahneman(2003) refers to bounded rationality as different geographic maps of the same territory. With respect to these boundaries of intuitive thinking, the judgements that people express, the actions that they take, and the mistakes that they commit depend on the monitoring and corrective functions of reason (system 2) as well as on the impressions and tendencies generated by intuition (system 1).

Kahneman and Tversky (1979) point out that agents' perceptions are reference-dependent; the perceived attributes of a focal stimulus reflect the contrast between that stimulus and the context of prior and concurrent stimuli. The standard economic theory assumes that the analysis of the utility of decision outcomes is determined entirely by the final wealth, and it is therefore reference-independent. Based on experimentation, Kahneman and Tversky (1979) concluded that people tend to change abruptly from risk-aversion to risk-seeking according to how the problem is presented. This feature cannot be explained by a utility function for wealth as preferences appear to be determined by attitudes to gains and losses defined relatively to a reference point. That is, they suggest an alternative theory of risk in which the carriers of utility are gains and losses (changes of wealth rather than states of wealth). This new theory is called *prospect theory*. The distinctive predictions of prospect theory follow from the shape of the value function defined on gains and losses. The value function is characterized by three features: (1) it is concave in the domain of gains, favoring risk aversion; (2) it is convex in the domain of losses, favoring risk-seeking; and (3) the function is sharply kinked at the reference point and loss-averse (steeper for losses than for gains by a factor of about 2-2.5 (Kahneman(2001), and Tversky and Kahneman(1992)). The activity of traders in stock markets fits the predictions of prospect theory very well. Traders are much more interested in short term realizations rather than final wealth.

Prospect theory is concerned with immediate outcomes, in contrast with utility theory, which defines outcomes as states or as changes with only future consequences. The value function of prospect theory presumably reflects an anticipation of the valence and intensity of the emotion that will be experienced at moments of transition from one state to another (Kahneman (2000)),and Mellers (2000)).

The affect heuristic is a concept that has been developed by Paul Slovic and his colleagues as a theory of how people assess risks (Alhakami and Slovic, 1994; Peters and Slovic, 1996; Finucane et al., 2000; Slovic, 2000; Slovic et al., 2002). These authors argue that people's decision-making is guided by the images and associated feelings that are induced by the decision-making process.

Research led by Donald MacGregor has investigated the applicability of the affect heuristic to understanding investor decision-making (MacGregor et al., 2000; Dreman et al., 2001;

[8] The notion of bounded rationality goes back to Simon(1957).

MacGregor, 2002). This research indicates that investors make consistent decisions with the predictions of the affect heuristic. The valuation of a company's equity appears to be influenced by whether the investor likes or dislikes the company. This effect is illustrated in a study by MacGregor et al (2000). The study involved 57 participants. Each participant gave an image rating for 20 industries, with the image rating ranging from Highly Negative to Highly Positive. The 20 industries selected included ten that were stock market high performers in the previous year, and ten that were stock market underperformers in the previous year. Participants were also asked to estimate the stock market performance of the industry in the previous financial year, the performance of the industry over the coming year, and to say whether they would be willing to buy into an IPO from a company in the industry. The results confirmed that image played a significant role in participants estimates of investment performance. Overall the image ratings were positively skewed, indicating that the overall sample of industries had a positive image. The average image rating was +0.56, based on a scale that ranged from -2.0 (Highly Negative) to +2.0 (Highly Positive). The results illustrated what the authors termed internal consistency. Affective rating was closely correlated with judgements of past performance and judgements of future performance and willingness to invest in an IPO. That is, a positive image was linked to good past performance, and led to a belief in future good performance, and a willingness to purchase future IPOs in the industry. However, while the link between image rating and judgements of past and future stock market performance are internally consistent according to the Affect Heuristic, this link is not consistent with rational/efficient investor decision-making. It is not rational to expect future equity price out-performance or under-performance based on past equity price out-performance or under-performance. Nor is it rational that a positive image of a company should lead to positive rating of a stock, as all available information, including the factors that led to the company having a positive image, are assumed to be already incorporated in equity prices. Thus, if a company has a negative image because it sells cigarettes, this negative image should not influence the evaluation of future returns for the companys equity. According to the Efficient Market Hypothesis, any predictable financial implications of this negative image will already be incorporated in the equity price.

There is some empirical support for the argument that the feelings induced by image, influence not only individual investor decision-making, but also equity prices. A survey by Shefrin (2001) of equity market professionals found that they appeared to predict the future price performance of a company's equity based on their image of the company. He argued that people were making the mistake of believing that stocks of good companies are representative of good stocks (p. 5). This finding is supportive of the Affect Heuristic, but contrary to efficient equity pricing, as it resulted in stocks with low risk being predicted to have high future returns, and stocks with high risk being predicted to have low future returns an inverse of the accepted positive relationship between risk and expected return (e.g. Sharpe, 1964). Some anomalies in finance can also be argued to be supportive of the affect heuristic and image influencing equity pricing. These anomalies include Cornells (2000) analysis of the pricing of Intel; and Cooper, Dimitrov and Raus (2001) analysis of the pricing of Internet companies following a name-change. Cornell (2000) investigated an Intel share price drop of 30 percent on 21st September 2000. The drop followed the company issuing a press release announcing a small slowdown in sales in the company's European operations. Cornell analyzed the press release the company issued and could not find any information that could justify such a fall . He also analysed the behaviour of analysts who followed and made investment recommendations on Intel. He found that analysts gave a higher rating to the equity when it was worth USD75 in August, than when it was worth USD40 at the end of September. Yet the company had not given sufficient information to indicate a dramatic slowdown in sales, just a minor slowdown in one market. Nor did the analysts justify their changed views using discounted cash flow analysis. Cornell states that it is difficult to understand how the analysts arrive at their estimates of fundamental value (p. 20). He goes on to claim that "analysts are in some sense rating the company, rather than the investment" (p. 22). Thus, analysts appear to have been evaluating Intel on the basis of its image, rather than on its investment potential. The study of equity returns following corporate name changes to Internet related dotcom names by Cooper, Dimitrov and Rau (2001) is also indicative of image influencing the investment decision. From a sample of 95 stocks over the period from June 1998 to July 1999, a positive abnormal equity return of 53 percent was found over the five days surrounding an announcement of a name change. The level of the return did not appear to be related to the level of involvement of the company with the Internet, indicating an element of irrationality by investors. The authors conclude that investors seem to be eager to be associated with the Internet at all costs. Internet stock investors appear to have been driven by their positive image of the Internet, and not by a quantitative assessment of the risks and expected returns associated with these stocks.

1.3 Intentionality, ambiguity and polysemous signals

An important concept needed to understand how emotions influence financial markets and illusionary finance is the philosophical concept of *intentionality* (Searle (2004)) as it relates to ambiguity and polysemous signals in a financial context.

The term intentionality refers to the the ability to realize that people's behavior is contingent upon what they believe the current state of affairs is, which do not always accord with reality (Dumbar et al. (2005)). Intentions in the psychological sense, cover mental states characterized by terms like *beliefs, intentions, suppositions, inferences, etc*

The world of contemporary neuroscience argue that two realities exit simultaneously: the objective world in which we live, and the subjective world constructed by the brain. Evolutionary psychologists and philosophers of mind have investigated the structures of intentionality in the theory of mind and have found that the brain has a capacity to take degenerate stimuli and organize them into coherent wholes. Moreover, it is possible to alter one's initial perception of an image. Four of the most famous examples of this phenomena are shown in figure 1.1 and 1.2 .

The face in figure 1.1 can be seen as either a person's face or the word "Liar" written in italics. This illusion is truly ambiguous because it is easy to see both possibilities and one's perception of the image will actually change as one stares at the picture. This illusion is unstable. The left picture in figure 1.1, only weakly resembles a human face, nonetheless most people will perceive it as a face.

In the left picture in figure 1.2. some people see a young woman, while others see an old hag[9], both are correct. The "duck- rabbit example " in figure 1.2 is a typical example of

[9]The young woman is facing away, towards the left, with her long hair flowing down her back. To visualize

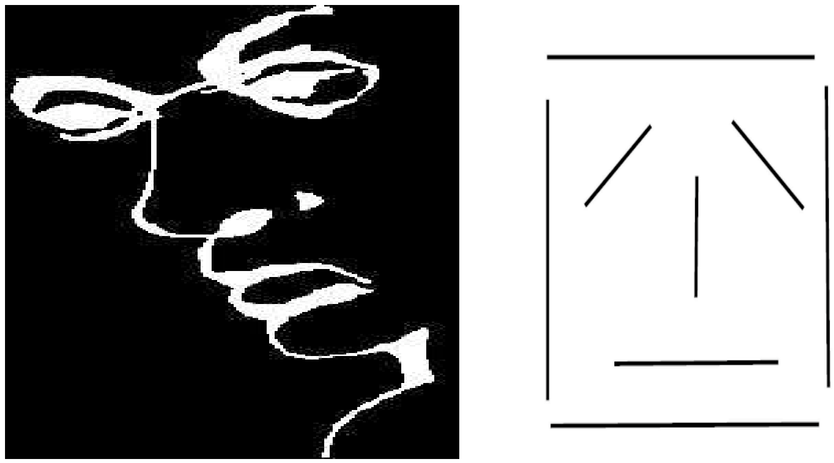


Figure 1.1: Ambiguous illusion

constant perceptual input. It can be perceived either as a duck or a rabbit. In both images in figure 1.2., one's perception will change as one stares at the pictures, and they are another unstable illusion.

In figure 1.1, the visual centers are designed to recognize patterns and if a particular form is vague, the brain will attempt to clarify the ambiguity by making a guess about what the object might be. In both images of figure 1.2, the brain takes only a few elements from what it sees to construct an internal image. It is an efficient mechanism, but one that leaves us vulnerable to misinterpretation.

Intentionality and polysemous objects of not only a visual nature are present in almost all the information humans need to decode. The properties of physical things tend to persist when the context are changed - but the 'significance' of a thought, idea or partial state of mind depends upon which other thoughts are active in time and what eventually emerges from the conflict with other senses. It is an illusion to assume a clear absolute distinction between 'expressing' and 'thinking' since expressing is itself an active process that involves simplifying and reconstructing a mental estate by detaching it from the more diffuse and variable part of its context.

The listener, too, must deal with ambiguity. For example everybody understands the "I wrote a note to my sister" despite the fact that the word "note" could mean a short letter or comment, a bank-note, a musical sound, an observation, a distinction, or a notoriety.

Many common words are ambiguous enough that even simple sentences can be understood in several ways.

The astronomer married the star.

It probably was a movie star, though the listener may have experienced a moment of confu-

the old hag, see the woman's chin as a giant nose, while her own petite nose becomes a wart. Her necklace becomes the hag's mouth, and her ear becomes the eye of the old hag.

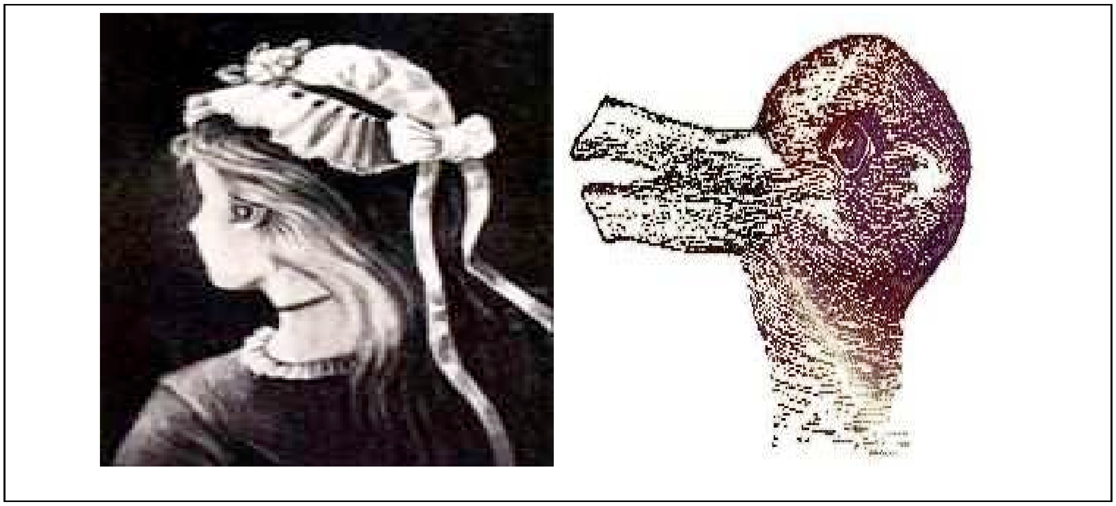


Figure 1.2: Brainteasers illusion

sion. The word "star" in this context is polysemous and can mean celestial body, a theatrical celebrity, or an object with a certain shape. The momentary confusion comes because the word astronomer give us an initial bias toward the celestial sense of "star" but that inhuman meaning causes conflict in our marriage-agent, and this soon leads to another, more consistent interpretation.

Now the problem is harder when a sentence contains two or more ambiguous words.

John shot two bucks.

Alone the word "shot" could refer either to shooting a gun or in American slang to making a bet. By itself the word 'buck" could mean either dollar or male deer. These alternatives permit at least four conceivable interpretations. Two of them are quite implausible because people rarely shot bullets at dollars or bet deer. But two are possible, because people do bet dollars and shoot at deer. So without more clues, we have no way to choose between these two plausible interpretations.

A finance related example of intentionality is provided below:

What is the value of MBS market (bottom area) in 2005? Is it less than 5000, or greater than 5000? Most people would say that it is less than 5000 when the reality is that it is more than 5000. Many investors take snap judgments based on graphs like this one which are normally provided by financial analysts.

Another example of polysemous information is the famous Alan Greespan's testimony before the Senate Banking Committee, in July 16, 2002 " An infectious greed seemed to grip much of our business community...It is not humans have become any more greedy than in generations past. It is that the avenues to express greed have grown so enormously" .

In the following chapters my goal is to show that when we take part in financial markets, we are exposed to emotional states which are accentuated with our self esteem, joy, arousal,

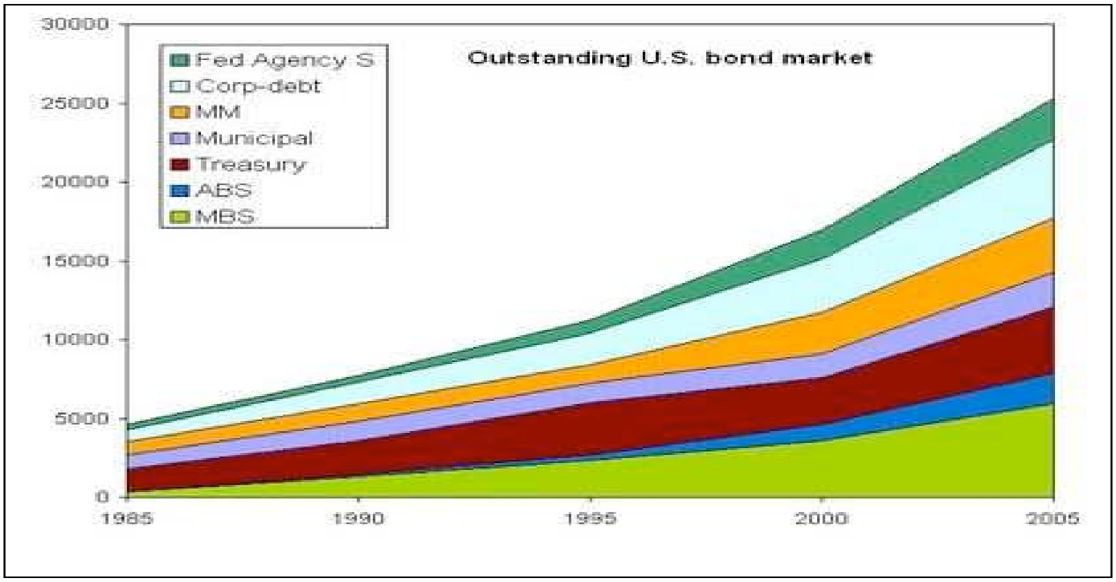


Figure 1.3: intentionality in finance

greed and fear; triggering emotes (cascades of feelings) and cognitive illusions. Since markets do not always work as predicted in financial textbooks most changes in prices are not fully communicated to all participants in the market place. As the ability of some people to fool other people will never disappear ensuring a perpetual cat and mouse game - rather than a fair contest.

On this particular journey I rely on papers written with several co-authors who provided me the joy of thrilling interaction, always open for discussions, which ultimately reinforces the final outcome of the papers.

Chapter two is an updated version of the paper "Emotions, Illusions and Neurofinance" written jointly with Ema Trifan. This second chapter closely relates with section 1.1 and provides a short introduction to the latest developments in cognitive psychology, neuroeconomics and evolutionary finance in the broad area of emotion research.

The third chapter, is based on the paper "Emotions, Bayesian Updating and Financial Decision Making" also written with Ema Trifan. The chapter relates with section 1.1 and presents a model where two groups of investors (rational and emotional investors), make decisions under uncertainty in order to ensure their survival in financial markets. Using a neurofinancial setting I show that when both populations fight for market capital, emotional traders tend not only to influence prices but also take over control from rational investors. The result implies that prices in financial markets could be seen more accurately as a thermometer of the market mood and emotions rather than simply informative signals as described in traditional financial theory.

The fourth chapter is based on the paper "Real or Illusionary markets?", an empirical testing of Emotes and Cognitive Illusion in Financial Markets" written with David Veredas. In this chapter I aim to integrate section 1.1 and 1.2 exploring the possibility of having emotes, units of emotions which serve to quantify emotional reactions embedded in financial prices. These emotes generate a cascade of feelings that develops into an emotional habit, affecting the significance about the informational content of prices. Using state space models and Markov chains, I test if these emotes trigger cognitive illusions, and whether they affect an investor's expectations, confidence and beliefs while making decisions under uncertainty.

The fifth chapter is also based on the paper "Emotions, Illusions and Neurofinance" written jointly with Ema Trifan. The chapter relates with section 1.2 and aims to give the foundations of illusionary finance focusing on cognitive illusions explaining why they are important when people make judgments under clouds of uncertainty.

The sixth chapter is based on the paper "Illusionary Finance and Trading Behavior" written with Erick Rengifo and Malika Hamadi. This chapter relates with section 1.2 and 1.3 and concentrates on traders who intentionally mislead other market participants by creating illusions in order to obtain a profit. I call this new concept illusionary finance and present an analysis of how illusions can be created and disseminated in financial markets based on certain psychological principles that explain 'agent' decisions under time pressure and polysemous signals. Furthermore, using simulations, I show how illusions can be incorporated, directly or indirectly, in the expected prices of traders.

The seventh and final chapter based on the paper "Hopes and Beliefs in Financial Markets: Can Illusions Survive in the Long run?" written with Paolo Colla presents a theoretical set-up in the spirit of the illusionary finance concept. Relying on the notions provided in section 1.2, 1.3 and empirical evidence that people often perceive relationships that in fact do not exist, I show that when markets are polluted with polysemous signals, a new category of traders named "Believers", who overestimate the relation between the polysemous signals and the asset payoff, arise and overcome rational traders.

In a nutshell this thesis investigates emotions, cognitive illusions, arousal and how these psychological factors influence financial markets. The most important contribution I would like to make is to leave the reader thinking about the morality of doing finance in the last decades and what they can do in order to avoid any form of illusionary finance from insiders. If that occurs my mission would be accomplished.

CHAPTER 2

Emotions, Neuroeconomics and Financial Markets

Emotions are a natural instinctive state of mind deriving from circumstances which have been extended beyond the judgement and decision making field. As we have seen in the previous chapter, emotions have become part of the new frontier in behavioral finance, and are certainly important to understand how markets work and how traders will react either to changes, or under the finding of an 'unawareness' state that can change their current perception of the current state of world.

This chapter aims to provide a short introduction to the main psychological, neurophysiological tools that have been recently incorporated in the study of financial markets and financial decision making, giving birth to a new subfield named neurofinance.

2.1 Emotions

An emotion can be defined as a complex multi-component episode that creates readiness to react (Frijda (1986) and Lazarus (1991)). All emotions represent in essence impulses to act, as suggested by the etymology of the word "emotion" itself. Its very root comes from the Latin *motere*, that means "to move"; the prefix -e refers to a direction namely "out" or "away". Hence, "emotion" stands for "to move away" and points out an implicit tendency to act.

Various terms have been used in the psychological literature to designate the notion of emotion. For instance, the concept of "feeling" is a synonym for emotion, albeit with a broader range. The term "affect" is used to indicate an even wider range of phenomena which are in some way connected to emotions, moods, disposition and preferences. There is a consensus to use the term "emotion" or "emotional episode" for states that last a limited amount of time, i.e. between a few minutes and a few hours, and the term "mood" for an emotional state that usually last for hours, days or weeks, sometimes as a low intensity background. Emotions are distinct from moods in several ways. For instance, they have a clear cause, i.e. they are about something or someone, they are particularly brief, and incorporate multiple components (Oakley and Jenkins, 1996).

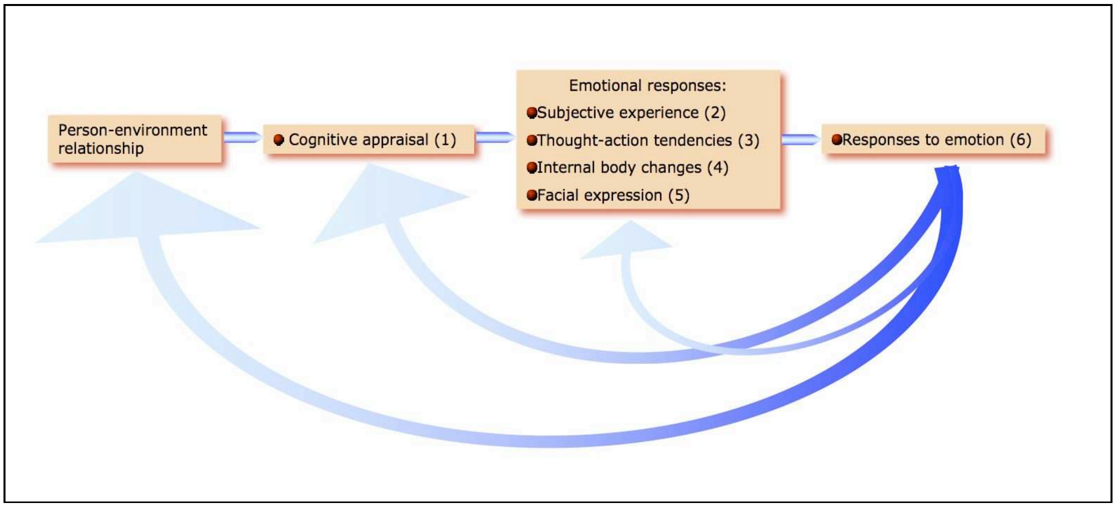


Figure 2.1: Components of Emotion

According to Lazarus (1991) and Rosemberg (1998) an emotion exhibits six basic components. It typically begins with a ***cognitive appraisal***, which illustrates the person's assessments of the personal meaning of his or her current circumstances. The cognitive appraisal triggers a cascade of responses which represent the other loosely connected components of an emotion.

The most frequently recognized of these responses is the ***subjective experience*** of the emotion, i.e. the affective state or feeling tone involved by the emotion. A third and closely related component includes ***thoughts and action tendencies*** or the urges to think and act in a certain way. A fourth component consists in the ***internal body reactions***, especially those of the autonomic nervous system, while a fifth component includes ***facial expressions***. The final element can be denoted as the responses to emotions and refers to how people cope with or react to their own emotion or the situation that elicits it.

The appraisal process plays an important role with respect to the assessment of a person whether his current relationship to the environment impinges on his goals of well being. If it does, the appraisal process translates the objective circumstance into a personally meaningful one, determining the type of emotion the person experiences and its intensity. All existent appraisal theories suggest that people's appraisal of a situation leads to the subjective experience of emotion, an arousal associated with it and other emotional responses associated with the subjective experience of the emotion. Yet, these theories differ in how they conceptualize the appraisal process. Following Smith, et al. (2003), we can distinguish between: (i) minimalist appraisal theories, which reduce the number of appraisal relations to minimum, often based on fundamental themes, and (ii) dimensional appraisal theories, which identify a range of appraisal dimensions considered to be sufficient in order to account for differences among emotions.

In this context, the theoretical debate concerning the question whether the appraisal process necessarily occurs consciously and deliberately has not yet reached a final response. We adopt here the position of Zajonc (1984) stating that cognitive appraisals within emotion processes are similar to other forms of cognition, thus, they exhibit a twofold origin: partly stemming from automatic processing, that lies outside conscious awareness, and partly from controlled conscious processing.

Neurological research about human behavior also supports the view that appraisals can occur both in a conscious and in an unconscious manner. The brain structure that plays a key role within emotions circuits is the amygdala, a small almond-shaped mass located in the lower brain and known as the place where emotional reactions are registered. Furthermore, as demonstrated by LeDoux and Phelps (2000), the amygdala is capable of responding to an alarming situation before the cortex. This points out the fact that sometimes we can experience an emotion before we know what is happening and why. Also, the amygdala monitors emotion-eliciting stimuli at an automatic unconscious level.

Although the initial appraisal process may occur outside conscious awareness, the subjective experience of emotion (the feeling component) is by definition within awareness. It appears that feelings guide behavior and information processing through the urges that accompany them. These urges are denoted as *thought-action tendencies* (Frederickson 1998) or just *action tendencies* (Fridja 1986, Lazarus 1991). Negative emotions lead to narrow and specific thought-actions, while positive ones make these tendencies turn to be more broad and open to possibilities. For example, the specific urge associated with fear (which is a negative emotion) is to escape the danger. In contrast, when we experience joy, our impulse is to be playful in general.

The subjective experience of emotions or feelings guides behavior, decision making and judgement. People tend to pay more attention to events that fit their current feelings than to events that do not. As a consequence, they learn more about the events that fit, or are congruent with their feelings. Moreover, experiencing a feeling during learning may increase the availability of memories that fit that feeling, so that the access to new material that also fits that feeling will be easier.

Recently, theorists (such as Lerner (2001), Tversky (1983)) have argued that feelings can affect the evaluation of other people and affect the judgement about the frequency of various risks. This occurs because emotions activate tendencies to reproduce the same cognitive appraisal that initially generated the emotion. Feeling fear for instance, leads to evaluate subsequent circumstances as uncertain and uncontrollable and thus, causes people to see future risks as more likely. Feelings lead people to selective attention and to learn feeling-congruent facts, which can also reinforce the initial emotion. This is valid for both negative and positive emotions, where the latter broaden the usual modes of thinking, making the finding of positive meaning in subsequent circumstances and the experience of further positive emotions more likely. In other words, the consequences of the subjective experience serves to perpetuate emotional states which entails downward spirals for negative emotions and upward spirals for positive ones.

2.1.1 The emotional mind

Many economists as well as emotions theorists (Goleman (1995), Loewenstein (2004)) have advanced the idea that humans have two minds: one that thinks and another one that feels. These two fundamentally different ways of knowing interact in order to construct our mental life. The rational mind is the mode of comprehension we are typically conscious of: more prominent in awareness, thoughtful, able to ponder and reflect. But alongside, there is another system of knowing, impulsive and powerful, sometimes illogical, the emotional mind.

The "heart" and "head" distinction made in romantic novels approximates the distinction between emotional-rational dichotomy. What your "heart" tells you to be true might be different of what your "mind" thinks to be right. This creates another level of "certainty". The rational-to-emotional control over mind depends on the intensity of the feeling (the more intense the feeling, the more dominant the emotional mind becomes and the more ineffectual the rational). This arrangement appears to have been generated in the course of the biological evolution being based on the evolutionary advantage to let emotions and intuitions guide our instantaneous responses in situations that put our life in danger, where waiting for the effortful and long lasting process of thinking to be accomplished can cost our lives.

Usually, there is a balance between emotional and rational minds. Emotions enter the operations of the rational mind providing useful signals, while reasoning refines and controls emotional inputs. Yet, the emotional and rational minds exhibit semi-independent faculties that reflect the operations of distinct but interconnected circuits in the brain. Moreover, the two minds appear to be very well coordinated most of the time. Feelings are essential to thoughts and thoughts to feelings, but it may happen that passions overcome rational mind.

The best two scientific models which explain how a large part of our actions can be emotionally driven are the seminal works on emotions by Paul Ekman and Seymour Epstein. Their emphasis on scientific evidence is different, but, taken together, they help to explain why the emotional mind has its own reasons and logic, hence offer a basis for distinguishing emotions from the rest of mental life.

The emotional mind appears to be much faster than the rational one, precluding the deliberate, analytic reflection that characterizes the thinking mind. Moreover, the emotional mind generates actions with a particular sense of certainty that stems from the simplified way of the emotional understanding of situations, which can entirely confuse the rational mind.

Since a stimulus can instantaneously trigger an emotion, the mechanism that appraises perception must be also very fast, in fact, automatic, so that it never enters conscious awareness. The costs of this rapid mode of perceptions consist in a reduction in accuracy. Thus, the emotional mind relies on first impressions and reacts on the overall picture or on the most striking aspects of it. Nevertheless, the great advantage is that the emotional mind can instantaneously read an emotional reality and to make intuitive snap judgments about who or what to be wary of, to trust, or who is in distress. Moreover, the emotional mind functions as a detection device for danger. Waiting for the rational mind to make vitally important judgements, can not only produce wrong results, but might bring death.

Because the rational mind is slower to register and respond that the emotional mind, the "first impulse" in an emotional situation is the one coming from the "heart" and not from the "head". However, there is also a second kind of emotional reaction, slower than the quick response, which becomes manifest and reflects first on the thoughts before it leads to feelings. This second emotional pathway is more deliberate, and there is an awareness of the thoughts that lead to it. In this kind of emotional reaction there is a more extended appraisal where the thoughts (cognition) play a key role in determining what emotions will be roused. Examples of this situations can be found when a trader acts as a bluffer or when we find someone "interesting".

In fast-response sequences, feelings seem to precede or to be simultaneous with thoughts. The rapid-fire emotional reaction takes over in situations that involve primal survival. This is the main power of such rapid decisions, they mobilize us in an instant to rise to an emergency, or to survive to the environment. It is important to note that among these situations there is not only danger and fear, but also love.

The logic of the emotional mind is associative, because it replaces the reality by elements that symbolize it or trigger a memory of it. That is why similes, metaphors, and images appraise directly to the emotional mind.

This logic of the emotional mind is well described by Freud in his concept of "primary process". Since the emotional mind follows its logic and its rules, with one element standing for another, things need not necessarily be defined by their objective identity, what matters is how they are perceived, i.e. things for our emotional mind are what they seem to be and what something reminds us of can be far more important that what it truly "is" . As Epstein pointed out, while the rational mind makes logical connections between causes and effects, the emotional mind is indiscriminate, connecting things that merely have similar striking features.

When some feature of an event seems similar to an emotionally charged memory from the past, the emotional mind responds by triggering the feeling that went with the remembered event. The emotional mind reacts to the present as if it were the past. The trouble is that, especially when the appraisal is fast and automatic, we may not realize that what was once the case is no longer so.

The working of the emotional mind is to a large degree state specific, dictated by the particular feeling ascendant at a given moment. Each feeling has its own distinct repertoire of thought reactions and even memories. These state specific repertories become most predominant in moments of intense emotions. One sign that such repertoire is active is selective memory.

2.1.2 The Somatic Marker Hypothesis

Based on his own studies of neurological patients who had both defects of decision-making and a disorder of emotion, Antonio Damasio postulated in his seminal book "Descartes' Error" the Somatic Marker hypothesis and is a cornerstone in neurological studies on emotions. This hypothesis postulates the loop of reason where emotion can assist reasoning rather than necessarily disturb it, as was commonly assumed.

Damasio proposes that the reasoning system evolved as an extension of the automatic emotional system with emotion playing diverse roles in the reasoning process.

Emotion has a role to play in intuition, the sort of rapid cognitive process in which a person comes to a particular conclusion without being aware of all the immediate logical steps. It is not necessarily the case that the knowledge of intermediate steps is absent, only that emotion delivers the conclusion so directly and rapidly that not much knowledge need to come to mind.

The quality of intuition depends on how well a person has reasoned in the past; on how well he has classified the events of his past experience in relation to the emotions that preceded and followed them: and also on how well he has reflected on the success or failure of his past emotion.

Intuition is just rapid cognition with the required knowledge partially swept under the carpet, all courtesy of emotion and much past practice.

As an example of how the somatic market hypothesis can assist in a situation that calls for a choice let's imagine that we are the CEO of a closed-end fund that buys-out companies and split them in pieces to sell them in parts. We are now facing the final stage for the buy-out of a company which belongs to a very good friend who really cares about his company. Nevertheless this deal is the best deal that we had seen in years. Maybe we will become famous because of this deal. What should we do?

The "high-reason" view, which is nothing else than the common sense view, will make us take hypothetical scenarios and perform a cost/benefit analysis of the situation. Mentally we are considering the consequences of each option at each point of the projected future and weight the ensuing gain and loses. We are not only thinking about financial outcomes, but also in terms of friendship. Since the latter loss will vary over time you must figure out its "depreciation rate". Also the idea of prestige and power are involved, which trigger more and more imaginary scenarios. As we can figure it out if we need to make a decision in a very short period of time, the mental cost/benefit analysis in its pure state[1] is not going to work since it will take an inordinately long time which we don't have.

Now imagine that before we can apply any kind of cost/benefit analysis to the premises and before we reason toward the solution of the problem something quite important happens: when the bad outcome connected with a given response comes into our mind, we experience an unpleasant gut feeling.

This unpleasant gut feeling is the somatic market hypothesis assisting us in speeding up our decision. Since gut feeling is about the body it receives the technical name of *somatic* and because it marks a mental image it will be called *marker*. Each time that our body generates this unpleasant gut feeling we will discard shortening the time that it takes to make a decision.

The idea of the somatic marker hypothesis is a general change of body state which includes modifications in both the visceral and the musculoskeletal system, induced by both neural signals and chemical signals, although the visceral component seems somewhat more critical in the musculoskeletal in the construction of a background and emotional estate. The feeling the body receives is given the technical name of 'somatic' and as it marks an image it is seen as a 'marker'.

The achievement of the somatic marker is to force attention on the negative or positive outcome that an action may lead to. Where the outcome is considered negative, it functions as an alarm signal which relays the message: Beware of the danger ahead if you choose this option.

This somatic marker probably increases the efficiency of the decision making process as a

[1]Considering all the possible alternatives, scenarios and weighting them

repository of feelings generated from secondary emotions. Those emotions and feelings have been connected, by learning, to predict future outcomes of certain scenarios.

When a negative somatic marker is juxtaposed to the outcome the combination functions as an alarm bell. In the opposite case of a positive somatic marker, the juxtaposition acts as a beacon of incentive behavior.

Somatic markers, in themselves, does not make a person deliberate, it only assists the deliberation by highlighting some options (either dangerous or favorable) and eliminating them rapidly for subsequent considerations.

Somatic markers are thus acquired by experience under the control of an internal preference system and under the influence of an external set of circumstances which includes not only the entities and events with which the organism must interact, but also social conventions and ethical rules.

The neural basis for the internal preference system consists of mostly innate regulatory dispositions, posed to ensure survival of the organism. The external set of circumstances encompasses the entities, physical environment and events relative to which the individual must act.

2.1.3 Brain Mechanism of Emotion

The schema that allows us to start making sense of brain and emotion was due to Descartes (1649). The mechanism is termed "the reflex". Events (stimuli) are able to excite sensory receptors, and these start messages along the sensory nerves to the brain where via a set of switches, they are rerouted along motor nerves to work the muscles. This system is designed so that the rerouting of messages produces a response more or less appropriate to the stimulus.

For understanding emotions we can take Descartes' ideas but we need to make two important modifications. The first idea is that actions prompted by emotions are not merely responses. They are self-regulating systems based on internal representations of goals and the comparison of events with these goal-primary appraisals. The second modification is that people as well as animals do not just make reflex responses to events, they generate plan-like patterns of action that are characteristics of the species.

A better supported theory of the relation of the parts of the brain to evolution was put by MacLean (1990, 1993), based on a speculative of Papez (1937). MacLean argued that the human forebrain is largely made up of three distinct systems. Each system developed initially in a distinctive phase of evolution. Then each region evolved further by accretion to what already existed. Each older structure developed links with later evolved structures but also continued to fulfil its original functions and remained dependent of its original mechanism.

Apart from the hypothalamus the earliest and most basic part of the forebrain is called the striatal region. This area becomes enlarged with the evolution of reptiles, argues MacLean, and it provides the basis for all animal behavior evolved from this stock. It is devoted to scheduling and generating outline scripts for airily life, and for behavior based on modifying these activities in response to actions of other members of the species. Based on the work of several researchers MacLean (1990) describes reptilian behavior as seen in modern lizards.

It includes preparation and establishment of a home site, marking and patrolling of ter-

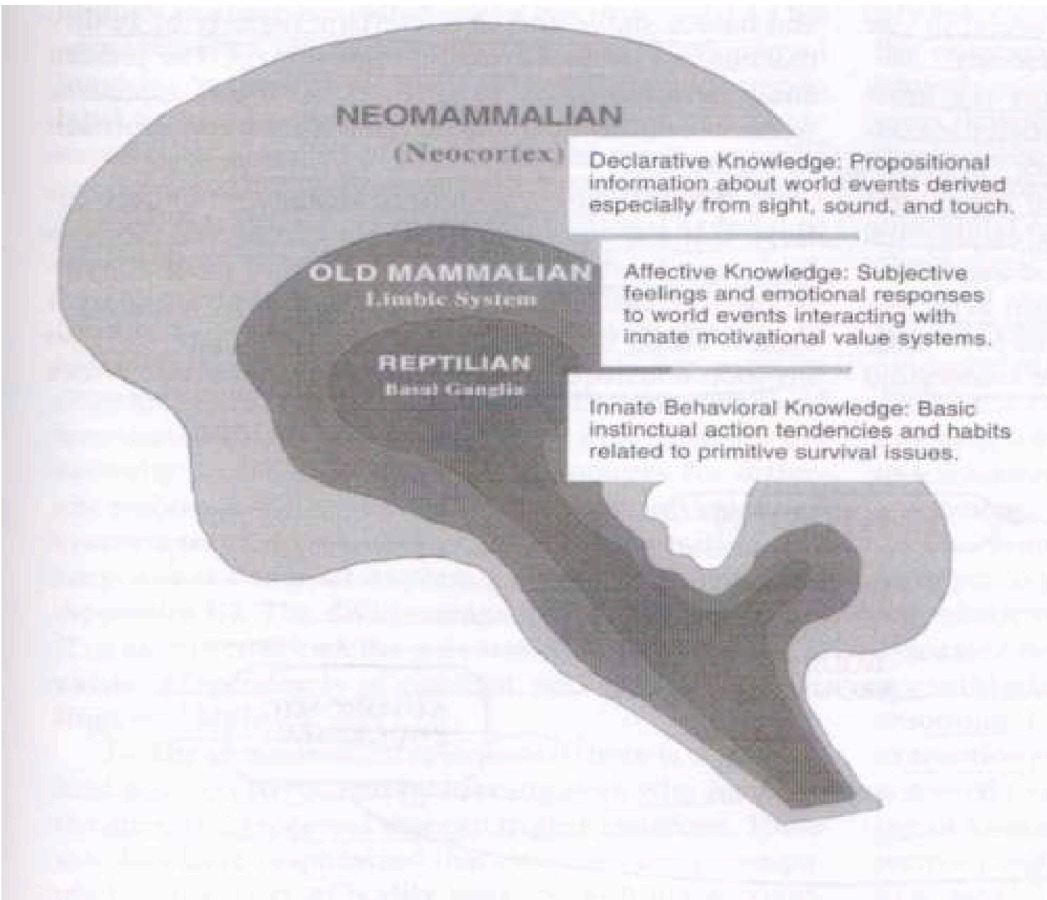


Figure 2.2: MacLean's Triune Brain (source: Panksepp)

ritory, formalized fighting in defence of territory, foraging, hunting, hoarding, forming social groups including hierarchies, greeting, grooming, mating, flocking and migration. Activities are scheduled by a master routine or script that each day involves walking and slow emergence, basking in the sun to increase body temperature, defecating, local foraging, an inactive period, foraging further afield, return to shelter and finally retirement for the night.

So the hypothesis drawn from this is the striatal region is involved in scheduling species-characteristic behavior patterns in mammals that are comparable of those of the reptiles.

The next move by MacLean (1993) was to analyze what mammals do that reptiles do not by showing that structures in their limbic system are more concerned with self-preservation with respect to the behavior of eating and competing with others for resources and with continuation of the species in the activities of mating, care giving and infant attachment. These latter functions add a principle of sociality to the lives of mammals which is largely absent from reptiles.

Maclean's second area of the forebrain, is called the *'limbic system'*. This area has a very close connections to the hypothalamus which not only controls the automatic nervous system (the part responsible for bodily changes, such as heart rate and sweating), but also the body's hormonal system via the pituitary gland, which is an extension of the hypothalamus.

MacLean argues that the limbic system underwent a new evolutionary enlargement with mammals, with the branching of their line from reptiles. Moreover, in humans the limbic system is thought to support the subjective experience of emotions. According to MacLean (1993) its main importance as a system is to bring stimuli from the outside world together with those inside the body. By nature this emotional system operates in terms of emotions eluding the grasp of the intellect because of it animalistic and primitive structure.

The neocortex (often referred to as the cortex) is where 80% of the brain is located and where the largest development in human beings take place.

In humans information from the outside world crosses over to the opposite side of the brain. So if someone looks directly to something vertical such as the edge of a door, then information about the world to the right of that edge is related via the thalamus to the visual regions at the rear of the cortex on the left side, while information about things to the right side is similarly related to the left side. In a comparable way the neutral pathways of action are crossed. So if you reach out with your right hand, this action is controlled from the left side of the cortex.

The right side of the cortex has been found to be more closely associated with the processing of emotional events. Whereas the perceptual areas are at the back of the cortex, experience and expression is represented towards the front. For experience there is no overall right-sided superiority for emotional events as compared with non-emotional ones. Instead some mechanisms related with the experience and expression of positive emotions are situated on the left side, and those related with negative emotions are on the right (Davison (1992)).

LeDoux (1993) argues that the amygdala is the central emotional computer for the brain, evaluating sensory input for its emotional significance - performing the functions of primary appraisals. The amygdala has connections to the right places to fulfil this role. It receives input from regions of the cortex concerned with visual recognition of objects and from regions concerned with recognition of sounds. The amygdala has also close connections to the hypothalamus, which from the work of Hess onwards has been also known to be concerned with emotional behavior.

The most distinctive part of LeDoux's hypothesis is that as well as inputs from the visual and auditory cortex, the amygdala receives visual and auditory inputs directly via the thalamus. This means that the amygdala receives sensory information that has not been processed by the cortex making it the core of a central network of emotional processing. Moreover LeDoux argues that the amygdala is responsible for assigning emotional significance to events and modulates the activity of many other parts of the brain, affecting arousal which as we have seen is one important component in an emotion.

2.2 Rationality and Emotions

Do emotions help us make good decisions or do they interfere? This simple question has been under rigorous examination for many years in social sciences, while in economics, as we have seen in the previous chapter it was left apart in search from a more axiomatic formalization of the field. After several decades of exhaustive research, we still haven't found a simple straight answer to this simple question and the answer is still being "it depends". The most popular hypothesis is that mild or moderate emotions help reasoning whereas higher amounts hurt. As we will see in this chapter emotions are often accompanied by autonomic nervous system arousal. According to one of the oldest findings in psychological research, the *The Yerders-Dodson Law* (Yerdes and Dodson (1908)), learning is at its best when stimulation or arousal is immediate (not too strong, not too weak).

There is another way to think about benefits and harms of emotions. Maybe benefit or harm in making decisions depends not on the amount of emotion, but on the type of reasoning we are talking about.

One of the first thing students learn in economics is to draw conclusions based in formal logic, for example "if A is true, then B is is true. If B is true, then C is true. Therefore, if A, then C". This sequence that seems obvious to any undergraduate student in economics does not proceed as smoothly when the elements A, B, C have emotional connotations.

Table 2.1: Reasoning in Emotional Situations

If-Then statement: "If someone is in a tragic situation, then she cries"

Additional statement	Question	Correct answer
1. Anne is in a tragic situation	Does she cry?	Yes
2. Gayle is not crying	Is she on a tragic situation?	No
3. Christine is in a happy situation	Does she cry?	Maybe (can't draw a conclusion)
4. Laura is crying	Is she on a tragic situation?	Maybe (can't draw a conclusion)

Before proceeding, it is important to understand that according to the if-then statement people in tragic situation cry, nothing is said about people in untragic situations, so logically we cannot draw a conclusion about Christine, who is happy.

In items 3 and 4, the idea that we can't draw a conclusion (which is supposed to be the logically correct answer) tends to be quite difficult for people to accept. Many people answer "no" to the type 3 item and "yes" to type 4 item just because results depend on emotional items. Thus, emotions seem not to help in logical reasoning.

Now decisions based on value judgments (for example which choice is better) are necessarily based on emotions. Moreover, decisions often depend on our expectations or beliefs of future emotions, that is people prefer the choice that will lead to an outcome that makes them and others happiest. In addition, as we have seen in the previous chapter when we introduced the risk-as-feeling hypothesis, people make different choices based on the emotions they feel at the time of making the decision. Specifically, anything that enhances fear, makes persons take precautions against the danger even if the objective probability of danger is low.

Decisions about buying or selling also yield to emotions. People actively use their current emotions as information when making decisions. If they feel good, then whatever they are currently contemplating seems good and valuable. If they feel bad, then there is a preponderation to think that the object is bad, too. Thus, emotions seems to play a crucial role when making choices based on values.

Finally given the link between emotions and our understanding of good and bad, we should expect emotions to be particularly important in moral reasoning. Let's consider the following three examples about making quick decisions:

1. A trolley car brakes have failed, and it is plunging toward five people who cannot move. You are standing at the switch that controls which track the trolley will enter at a junction. If you leave the switch alone, the five people will be killed. If you pull the switch you send the trolley onto another track where only one person is standing. What would you do?

2. Again, an out-of-control trolley is plunging downhill toward five people who cannot move. This time there is no switch, but you are standing on a footbridge above the track. You consider diving onto the trolley track to stop the trolley sacrificing your life to save the other five, but "unfortunately" you are not heavy enough. However, standing next to you is a very large wrestler, whose mass would surely stop the trolley. Would you push this person off the bridge to stop the trolley?

3. You are one of the six people on a lifeboat in icy water. The boat was built to hold only five, and is beginning to sink. The person sitting next to you is precariously balanced on the edge of the boat and not paying attention. Should you push this person, saving yourself and four others?

From a practical standpoint, all the cases have the same dilemma, as you will be killing one person while saving five. Yet far more people say it is okay to pull the switch in the first case rather than to push the stranger. However why is pulling the switch morally better than pushing the stranger? Apparently the idea of putting your hands on a stranger to push that person to a painful death is emotionally repugnant even if the consequences seems good overall. But is that explanation rational?

In the third case the big difference is that now *the reader* is one of those to be saved. Most of the people will decide to push the other stranger even though it is a difficult decision and there will be a guiltiness feeling afterwards. Greene et. al. (2004) have found that when people are thinking about this decision, the process activates the prefrontal cortex and the areas of the brain which are know to react to emotional arousal.

Let's consider now judgments that involve just to decide whether or not other people made acceptable decisions.

This example is based on Haidt (2001): *Mark and Julia are brother and sister, college students traveling together on a summer vacation. One night they are in a beach cabin, and* *they decide to have sex with each other. Julia is already taking birth control pills, but Mark uses a condom anyway. They both enjoy the experience, although they decided to they will not do it again. They keep this night as their especial secret, and neither one feels hurt with the experience.*

According to Haidt, Most people will immediately scream "Oh NO!!!! wrong, WRONG!", but when they are asked about rational explanations they cannot truly find them. The possibility of Julia getting pregnant is unrealistic (they used two dependable forms of birth control). The objection that they would be emotionally scared with the experience doesnt seems fair either since is explicitly stated that they both enjoyed it and neither was emotionally hurt. Haidt (2001) showed that if people are honest, they will admit that the only reason for saying that they were wrong is because it feels wrong. The idea of of sex between siblings is repulsive in every culture and it is a built-in taboo that evolved in prehistoric times. However, the important point is how people in general try to find a rational explanation for what is really an emotional decision. Moreover, when face with this type of decisions it is striking that facts seem almost irrelevant.

The crucial point that these examples want to make is if it is wrong to rely in emotional decisions. Unfortunately there is no single answer to that question. Defenders of the rational school would say that emotions are in the way of the "right" decision. However if we rely in evolutionary evidence (Dunbar(2005) and Damasio (1994)) we will believe that presumably emotions evolved because they provide benefits in most situations, and one of the benefits is that they help the organisms to survive and produce healthy offspring. It *feels* wrong to push someone off a lifeboat or to have sex with your brother or sister, and almost all the time it really *is* a very wrong idea. Emotions may not always be right, but at least they prepare the organism for a quick, probably useful, response.

2.3 Summary

The purpose of this chapter is to present a short introduction to the psychology and neurophysiology of emotions. We have also established the dichotomy about rational and emotional decisions, on which the next chapters will be built.

When we are confronted with sudden stimulus, or we have a decision to make, often our emotions respond quickly, before we have consciously identified the stimulus or cognitively pondered the decision. Our emotions are useful guide in such cases, they alert us to danger or urge us toward a quick response that is likely to be good. Presumably, emotions evolved precisely for this purpose, to prepare us for vigorous, usually correct responses when we have to act quickly.

The problem is that quick emotional decisions sometimes differ from the decisions a person would made if they thought out the situation rationally and leisurely. The difficulty is to know when to follow our emotion and when to override them.

The dichotomy of if it is better to make decisions based on rationality or in gut feelings is still an arduous debate in economics, and it is magnified in finance because of the radical uncertainties of finance. Financial decisions rely on promises of an uncertain reliability (future cash flows) and competitive financial players live and die upon predicting future outcomes which are unknowable, no matter how rational their calculations of past information are.

CHAPTER 3

Emotions, Bayesian Inference, and Financial Decision Making

We present in this chapter a model which relies on the neuro-financial tools presented in the previous chapter. Based on an evolutionary finance environment, we present the world as an ecology in which two species named rational and emotional investors are compelled to make decisions under uncertainty in order to ensure their survival.

The main motivation of this chapter is to show that, when different investor types fight for survival, emotional traders tend not only to influence prices but also to have a much more developed adaptive mechanism than their rational peers, in spite of their apparently simplistic demand strategy and distorted revision of beliefs. Our results imply that prices in financial markets could be seen more accurately as a thermometer of the market mood and emotions rather than as simple informative signals as stated in traditional financial theory.

3.1 Introduction

In contrast to the dominant view of the negative influence of emotions (Smith (1759), Peter and Slovic (2000)), new research in neuroeconomics, and psychophysiology have highlighted the benefits emotions bring to decision making. The purpose of this chapter is in line with these recent findings by showing the important role of emotions in financial decision making as an adaptive mechanism. Also, we are interested in the use of moods and emotions as an analytical toolbox employed to establish trading strategies that appear to be as good as (if not better than) purely rational ones, in order to ensure survival in competitive environments.

As we have seen in the previous chapters, emotions are important adaptive toolboxes in speeding up the decision-making process. Neuroscientists document the existence of a permanent interaction between the neural systems of both the thinking and the feeling parts of the human brain. Moreover, due to the higher speed of emotional responses to external stimuli compared to the reasoning responses, or to a sufficiently high intensity of emotions, in certain situations human actions can be developed without thinking (Bosman and van Winden (2005)).

Rational decision making has always been associated with the concept of Bayesian inference which can be seen as the cornerstone of modern decision theory, given the importance in assisting agents to make rational decisions under uncertainty. In a nutshell, Bayes rules assist agents in amending prior beliefs by a signal in which new information is condensed.

In economics and more specifically in finance, the traditional theory relies on the assumption that investors are able to process the relevant information at their disposal and form coherent probability judgments on the basis of the Bayes rule. Therefore, in the traditional framework, all market information is reflected in prices, which become fully informative[1]. Thus, every opportunity to make profits by forecasting future prices is ruled out.

Bayesian inference helps financial decision making when there is a need to update a probability estimate in the light of new evidence. Psychologists have wondered if the Bayes rule truly describes how people revise their beliefs. Following Birnbaum (2004), we can classify psychologist's opinions in three periods: an early period which supported the Bayesian rule as a rough descriptive model of how humans combine and update evidence; a second period dominated by Kahneman and Tversky's assertion that people do not use base rates or respond to differences in validity of sources of evidence; [2] and a more recent period showing that people indeed rely on base rates and source credibility, but combine this information by means of an averaging model which is not consistent with the Bayes rule. The distinctive feature of the averaging model is that the directional impact of information depends on the relation between the new evidence and the current opinion (Birnbaum and Stegner (1979), Anderson (1981)).

For numerous years economics has relied on the fallacy that people apply rational calculation to economic decisions, ruling their life by economic models. Numerous empirical studies have emphasized the perpetuated existence of "not fully" or "quasi rational" investors, who employ a small number of simple and quick rules of thumb in order to make decisions under uncertainty. These rules are denoted in psychological terms as heuristics and prove to be useful in practice, especially when decisions have to be made under time constraints. However, they can sometimes lead to systematic mistakes (biases).

Within the last years, a new paradigm which tries to integrate the classical financial theory with the behavioral perspective has been developed (Lo (2004)). This new paradigm is based on Darwin's theory on the evolution of species and considers individuals as organisms that try to maximize the survival of their species. Thus, their behavior is not intrinsic and exogenous, but evolves by natural selection and is adapted to the particular environment. Particularly during the decision making process, individuals develop heuristics in order to maximize the efficiency of their responses to uncertainty. However, since the environment is constantly changing, we can observe behavioral biases given the maladaptation to new circumstances.

Our intention is to extend the adaptive market hypothesis proposed by Lo (2004), by

[1] This is commonly known as the efficient market hypothesis (Samuelson (1969), Fama (1970)).

[2] Please refer to Chapter 5, Section 5.1.1 for an in deep coverage of the base rate fallacy.

incorporating market microstructure features and the role of emotions in financial decision making. Accordingly, we design the ecology of the market as a population consisting of three types of investors: rational investors, emotional investors and noise traders. These species differ in the way they interpret information and make decisions.

Concerning the information updating process, rational investors consider both prior and current information to be equally important in order to ascertain the current market price, while emotional investors under(over)weight the prior relative to the current information. In essence, emotional investors are quite young and self confident. Most of them have no formal education concerning financial markets. Thus, they do not analyze the market development using sophisticated tools, relying instead on their own intuition and experience in the market. The market maker fixes prices efficiently, in linear dependence on the observed total order flow.

Regarding the strategies employed in order to ascertain their demands, rational investors maximize their expected group-profits, emotional investors trade in accordance with their subjective evaluation of the returns, which relies on affective processes, and noise traders act randomly.

We believe that these three investor categories resemble a real market, where we find professional traders who dispose of sufficient resources and motivation in order to make decisions in a way approaching the rational type, as well as trades impelled by exogenous reasons, resembling the random actions of the noise traders in our model. Moreover, some market participants may speculate in reality on public information in an intuitive and affect-driven way.

The original contribution of this chapter is to show that in the ecology of the market where not only rational investors and noise traders, but also a new class of investors named emotional interact, both rational and emotional investors can influence prices and survive in the long-run. Additionally this chapter shows that different types of market participants hold distinct beliefs on returns, which are directly revealed in their demand strategies and thus incorporated into prices, affecting the informational content of prices.

We illustrate our model in an experimental environment showing that the emotional group's wealth can exhibit higher values than the rational one. This result supports the hypothesis concerning the survival (and dominance) of emotional traders in the market, in spite of their apparently simplistic strategy and "distorted" revision of beliefs.

The remainder of the chapter is organized as follows: Section 2 presents the model of the ecology of the market including information-updating, pricing mechanism and demand strategies. The experimental design, encompassing the simulation results with respect to log-returns, group-demands and group-wealths is shown in Section 3. Section 4 summarizes the most important conclusions.

3.2 The model

This section shows how the subjective beliefs of different types of market participants are translated into prices. Our starting point is the modeling of the mind-set (or genesis of group-specific opinions) with respect to the evolution of market prices. Afterwards, we describe how investors' thoughts are translated into actions, that is how subjective opinions flow into idiosyncratic demand strategies. Then, we show how investor demands assemble the total order flow that periodically arrives to the market maker and how this order flow generates market prices. In other words, this section maps the entire process of price emergence, starting from its very first origin, the minds of each market participant, going through their actions and reaching into market prices by means of the mechanisms employed by the market maker to fix prices. Thus, we can finally quantify the influence of different investor types on market prices.

We consider the population of market participants as consisting in three categories of investors active in the market: *rational investors*, *emotional investors* and *noise traders*. Rational investors act according to traditional principles such as belief formation in a Bayesian manner and profit maximization. In contrast, emotional investors follow their intuition in evaluating the importance of different informational sources they access in order to revise their beliefs, as well as in translating these beliefs into periodical demands. Noise traders act randomly, being driven by exogenous reasons and their opinions do not influence the price evolution.

In the following subsections we present the information updating processes and the decisional mechanisms of the market participants and analyze their impact on price formation.

3.2.1 Information updating

We are primarily interested in how investors perceive information that is subsequently incorporated in their trading strategies. Our focus is on the mental processes developed by rational and emotional investors in order to create and revise their strategies. Since noise traders act randomly, we are not interested in the way they perceive information.

Rational and emotional investors interpret the same (public) market information in different ways. We assume that there is just an information-set considered to be public (common) and we are interested in how different investor groups perceive this common information. In other words, the aim of this chapter is not to focus about information asymmetries due to differences in the amount of information available for the different players, but on how their individual perception generates differences in the interpretation of the same information. Formally, different beliefs are emphasized by distinct probability density functions[3], where the return densities in the view of the rational and emotional investors are denoted as $f(r_t^r|\mathcal{F}_{t-1})$ and $f(r_t^e|\mathcal{F}_{t-1})$. In this context, $r_t = log(p_t) - log(p_{t-1})$ stands for log-returns, while $\mathcal{F}_{t-1}$ refers to the available market information at date t (consisting of past prices $\mathcal{F}_{t-1} = \{p_{t-1}, p_{t-2}, \ldots, p_0\}$). The parameters r_t^r and r_t^e designate what we call rational and emotional subjective perception (or belief) about returns, respectively. We note that the notion of "perception about returns" shall be understood in this context in the sense of "subjective view over returns" and does not strictly refer to expectations in a formal statistical sense.[4]

Like in the traditional Bayesian framework, rational investors consider both prior and current information to be equally important in order to ascertain the current market price. In contrast, judgements of the emotional investors are under the influence of their current affective state. They rely more on their intuition or feeling about past and new information in order to make judgments and choices.

[3] Henceforth, the superscripts r and e emphasize the subjectivity of the rational and emotional view, respectively.

[4] What we are truly interested in is in the whole return distribution as perceived by the two main investor categories considered in this section.

Rational investors combine prior and current information in a balanced way, while emotional investors can over(under)appreciate the importance of past information with respect to new evidence. Formally, we use distinct functions for this two information sources: the functions g stand for the distributions of log-returns conditional on the subjective beliefs (and correspond to the current information), while the φ-s account for the prior distribution of these subjective beliefs (which corresponds to the prior information).[5] As stated above, r_t^r and r_t^e respectively, denote the perceived rational and emotional current returns, while r_t^n is rather a formal notation meant to facilitate the understanding of price formation and the comparison between the behavior of different market participants.[6]

We then define

$$f^r(r_t|\mathcal{F}_{t-1}) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g^r(r_t|r_t^r, r_t^e, r_t^n, \mathcal{F}_{t-1})\varphi^r(r_t^r|\mathcal{F}_{t-1})\varphi^r(r_t^e|\mathcal{F}_{t-1})\varphi^r(r_t^n|\mathcal{F}_{t-1})dr_t^r dr_t^e dr_t^n \tag{3.1a}$$

$$f^e(r_t|\mathcal{F}_{t-1}) = \int_{-\infty}^{\infty} [g^e(r_t|r_t^e, \mathcal{F}_{t-1})]^b[\varphi^e(r_t^e|\mathcal{F}_{t-1})]^a dr_t^e. \tag{3.1b}$$

As mentioned above, the densities f^i for each of the rational and emotional investor groups $i \in \{r, e\}$ arise as a combination between prior information φ^i and what we can denote as current information g^i, each of them in the group-specific interpretation of the two investor types. Concerning the combination of these two information sources, what distinguishes the emotional investors of their rational peers is that they put different weights on the perceived φ and g. Concerning the expressions of φ^i and g^i, we note some formal differences. For instance, if both rational and emotional investors account for the existence of different investors trading in the market, then both φ^r and φ^e should be functions of all group-specific beliefs r_t^r, r_t^e and r_t^n (e.g. $\varphi^i(r_t^r, r_t^e, r_t^n|\mathcal{F}_{t-1}), \forall i \in \{r, e\}$), and as well both g^r and g^e should describe the evolution of the returns r_t subject to all r_t^r, r_t^e and r_t^n (e.g. $g^i(r_t|r_t^r, r_t^e, r_t^n, \mathcal{F}_{t-1}), \forall i \in \{r, e\}$). However, while rational investors are indeed aware of the existence of different strategies in the market, emotional investors are not concerned with the belief formation by other investors. Thus, we assume that rational investors consider their group-specific prior subjective belief to be independent

$$\varphi^r(r_t^r, r_t^e, r_t^n|\mathcal{F}_{t-1}) = \varphi^r(r_t^r|\mathcal{F}_{t-1})\varphi^r(r_t^e|\mathcal{F}_{t-1})\varphi^r(r_t^n|\mathcal{F}_{t-1}),$$

and that g^r is indeed a function of the form $g^r(r_t|r_t^r, r_t^e, r_t^n, \mathcal{F}_{t-1})$ that will be defined below. In the contrast, emotional investors treat the prior rational and the prior noise trader perceptions as being uninformative, which reduces their prior to $\varphi^e(r_t^e|\mathcal{F}_{t-1})$, and their g^e can be also formally expressed as $g^e(r_t|r_t^e, \mathcal{F}_{t-1})$.

[5]The emotional belief formation rule is defined in the style of Grether (1980) and Shefrin (2005). In spite of the similitude with the Bayesian-like formula used by our rational investors, we note that emotional investors perform a different type of updating that we call affective (adaptive), inspired by the averaging model of Birnbaum and Stegner (1979).

[6]In reality, noise traders act randomly, hence their beliefs are not of interest for the price evolution and they do not develop a well-defined demand strategy.

The power-weights a and b allow us to formally model the idea of affect-driven belief formation. They are chosen in order to satisfy[7]

$$\begin{aligned} &\int_{-\infty}^{\infty} f^e(r_t|\mathcal{F}_{t-})dr_t = 1 \\ &a, b > 0. \end{aligned} \tag{3.2}$$

When $b \geq a > 0$, emotional investors react myopically to current market events, given that the affective reaction carried by new information prevails. In contrast, when $a \geq b > 0$, investors consider that new evidence is not as important as their subjective beliefs formed in the past.

In order to derive the subjective distributions (3.1), we first specify the two different informational components (i.e. the densities of group-specific prior expectations φ and the conditional current information distributions g) in the view of rational and emotional investors.

(i) The prior information φ^r and φ^e

Rational and emotional investors may assign different distribution laws for the prior subjective densities from equations (3.1). We consider the simplest case with normal distributions (with different parameters) and equivalence between the prior distributions of r_t^e in the rational and emotional view. Also, given that noise traders are known to act randomly, the estimated mean of their prior expectations r_t^n reduces to zero in the view of rational investors. Thus,

$$\varphi^r(r_t^r|\mathcal{F}_{t-1}): \qquad r_t^r|\mathcal{F}_{t-1} \sim N(\tilde{r}_{t-1}^r, (\sigma^r)^2) \tag{3.3a}$$
$$\varphi^r(r_t^e|\mathcal{F}_{t-1}): \qquad r_t^e|\mathcal{F}_{t-1} \sim N(\tilde{r}_{t-1}^e, (\sigma^e)^2) \tag{3.3b}$$
$$\varphi^r(r_t^n|\mathcal{F}_{t-1}): \qquad r_t^n|\mathcal{F}_{t-1} \sim N(0, (\sigma^n)^2), \tag{3.3c}$$

for the rational investors and

$$\varphi^e(r_t^e|\mathcal{F}_{t-1}) \quad [\equiv \varphi^r(r_t^e|\mathcal{F}_{t-1})]: \qquad r_t^e|\mathcal{F}_{t-1} \sim N(\tilde{r}_{t-1}^e, (\sigma^e)^2), \tag{3.4}$$

for the emotional investors.

(ii) The current information g^r and g^e

While rational investors are aware of the existence of different investor types who hold different opinions about price evolution, emotional investors focus merely on their own intuition and do not account for other opinions in the market. Therefore, in the view of rational investors, conditional log-returns are normally distributed around a linear combination of subjective expectations originating from each investor type active in the market (r_t^r, r_t^e and r_t^n) and encompass an exogenous noise component. However, in the view of emotional investors, the distribution g^e centers only on the own affective expectation of emotional investors and encompasses exogenous noise as g^r

$$g^r: \qquad r_t|r_t^r, r_t^e, r_t^n, \mathcal{F}_{t-1} \sim N(c_{t-1} + c^r r_t^r + c^e r_t^e + c^n r_t^n, \sigma^2) \tag{3.5a}$$
$$g^e: \qquad r_t|r_t^r, r_t^e, r_t^n, \mathcal{F}_{t-1} \sim N(k_{t-1} + k^e r_t^e, \sigma^2), \tag{3.5b}$$

[7]The marginal cases of mathematical interest $a = 0$ and $b = 0$ appear to be irrelevant from an economic perspective, given that either completely uninformative prior or uninformative current information is hardly to be expected in conjunction with real decision problems. Shefrin (2005) suggests as a more realistic assumption the following values: $b > 1$ and $0 < a < 1$.

where c^r, c^e, c^n and, k^e represent the weights of each group-specific beliefs in the view of the rational and emotional investors. Also, c_{t-1} and k_{t-1} denote constant terms relying on the available (past) information.

(iii) The derivation of the subjective densities f^r and f^e [(i)+(ii)]

Finally, the subjective densities $f^r(r_t|\mathcal{F}_t)$ and $f^e(r_t|\mathcal{F}_t)$ are derived by incorporating equations (3.3)-(3.5) into equations (3.1) and result in

$$f^r : r_t|\mathcal{F}_{t-1} \sim N(c_{t-1} + c^r\tilde{r}^r_{t-1} + c^e\tilde{r}^e_{t-1}, \sigma^2 + (c^r\sigma^r)^2 + (c^e\sigma^e)^2 + (c^n\sigma^n)^2) \tag{3.6a}$$

$$f^e : r_t|\mathcal{F}_{t-1} \sim N\left(k_{t-1} + k^e\tilde{r}^e_{t-1}, \frac{\sigma^2}{b} + \frac{(k^e\sigma^e)^2}{a}\right). \tag{3.6b}$$

We note the discrepancy between rational and emotional views over returns distribution, which is mainly driven by emotions. Rational investors allow for the existence of different opinions in the market and combine past and new information in a balanced way. In contrast, emotional investors guide their beliefs by means of their current affective state, which leads to a focussing on the own price perception and an impulsive over(under)weighting of one of the informational sources considered in order to revise beliefs. Thus, the behavioral power weights a and b have an impact on the variance of the emotionally perceived returns.

As already mentioned, rational investors recognize the active presence of other investor categories in the market, from which some trade randomly and others follow their intuition. Furthermore, the variances of their priors about both emotional and noise traders are considered to be identical and denoted by $\sigma^e = \sigma^n = \sigma^\eta$. However, this does not make emotional investors act as pure noise traders in the view of their rational peers. Relying on their intuition, emotional investors add a deterministic component to their expectations (and thus demands), which is different from $\tilde{r}^n_{t-1} = 0$ (see equation (3.6)).

For reasons of mathematical simplicity, the model of rational and emotional thinking processes presented in this subsection yields a simplistic, myopic logic in a rather static framework.

3.2.2 Pricing mechanism

In order to describe the demand strategies, we first formulate the pricing equation for setting the current price. Relying on commonly accepted market microstructure approaches (i.e. Kyle (1985), Farmer (2002)), we assume that prices are fixed efficiently, in linear dependence on the total flow of market orders issued by the investors

$$r_t = \lambda Q_t, \tag{3.7}$$

where we consider zero initial returns and λ represents the inverse market liquidity and Q_t is the total order flow observed at date t.

The total order flow represents the sum of market orders currently issued by investors

$$Q_t = n^r q^r_t + n^e q^e_t + (1 - n^r - n^e)q^n_t, \tag{3.8}$$

where q^r_t, q^e_t and q^n_t represent the demands of the rational investors, emotional investors and noise traders and n^r and n^e being the dimensions of the rational and emotional group, respectively. (Henceforth, we consider $n^r, n^e \in (0, 1)$, so that they can be interpreted as well as proportions to the totality of market participants.) .

3.2.3 Asset demands

The formation of subjective beliefs described in Subsection 3.2.1 directly influences the actions of the investors. These actions center on investment decisions which are periodically undertaken and followed by each group-specific logic of concrete strategies of asset demand. This subsection specifies the demand strategies of each investor type active in the market, which generate the total order flow arriving at the market maker as formulated in equation (3.8).

Rational decisions are dominated by reasoning (which complies with the complex of cognitive processes denoted as System 2 within the Kahneman's (2003) two-system model presented in chapter 1). Rational investors act in accordance with the traditional principles of expected profit maximization. The trading strategy of the pure noise traders is mostly driven by exogenous reasons (such as the need of liquidity) and therefore based on purely random actions. Emotional investors care about their affective reactions and intuitions in devising their demand. From a psychological point of view, their cognitive processes are dominated by affect (Loewenstein and Lerner (2003)) and intuition (denoted as System 1 in Kahneman (2003)).

We consider investors to be mainly concerned not only with individual survival, but also with the survival of their own kind. Thus, rational investors aim the maximization of their subjectively expected current group-profits, which can be formulated as the product of the current demand and the difference between "subjective" and "fundamental" beliefs.

$$q_t^r = \arg\max_{q_t}\{n^r q_t(P_t^r - \tilde{P}_t)\},$$

where P_t^r stands for the subjective price belief (corresponding to the view over returns r_t^r) and emerges from the idiosyncratic interpretation of public information by rational investors (as described in Subsection 3.2.1). What rational investors try to exploit is the difference between their subjective view over the price evolution P_t^r and what they think the market should consider as plausible price evolution $\tilde{P}_t$ (i.e the perceived fundamental price). Since the current price P_t is not yet fixed when investors formulate their current demands, this difference is what generates profit according to rational investors' logic.

In other words, rational investors are aware of the existence of different demand strategies in the market and incorporate it in their own subjective view of the price evolution (P_t^r). Conditional on past information at date t, their "subjective" belief of the price evolution is thus $P_t^r \simeq P_{t-1}(1 + r_t^r)$. However, they perceive the market as dysfunctional and believe that since their analysis comes from introspection, they are better informed than the other markets participants. Thus, they should be the only smart enough type to predict and influence the prices. Moreover in their own perception, based in what traditional financial theory ensures, emotional and noise traders do not have a coherent strategy and they will be wiped out soon (see for instance Montier(2002), Goldberg et al (2001). Thus, the "perceived fundamental price" of rational investors is given by $\tilde{P}_t \simeq P_{t-1}(1+\lambda n^r q_t^r)$ and represents the belief of rational investors that in an efficient market they should be the only type capable to predict and influence the order flow in Equation (3.8) and hence the prices. In sum, rational investor base their strategy in what traditional financial theory ensures and try to obtain a profit arbitraging against the market dysfunctionality.

Hence, the first and second order maximization conditions reduce to[8]

$$q_t^r = \arg\max_{q_t}\{q_t P_{t-1}(r_t^r - \lambda n^r q_t)\} = \frac{1}{2\lambda n^r} r_t^r = \beta^r r_t^r \tag{3.9a}$$

$$\lambda > 0, \tag{3.9b}$$

where

$$\beta^r = \frac{1}{2\lambda n^r} \tag{3.10}$$

stands for the sensitivity of the rational demand to price movements and is proportional to the market liquidity and inversely proportional to the dimension of the rational group. Therefore, a more liquid market gives rise to an increase in the rational demand. This corresponds to the empirical finding that rational strategies are more successful in liquid markets.

Equation (3.9a) shows that, acting as maximizers of the subjectively expected group-profits, rational investors get around using an ordered-based value strategy (as in Farmer (2002)). This strategy aims to linearly exploit the difference between subjective beliefs and the perceived fundamental price. The intuition behind this strategy can be traced back to the natural tendency to buy, as long as assets appear to be low priced relative to their own speculation, and to sell otherwise.

According to equation (3.6a), rational beliefs can be formulated as

$$r_t^r = c_{t-1} + c^r \tilde{r}_{t-1}^r + c^e \tilde{r}_{t-1}^e + \zeta_t + c^r \epsilon_t + c^e \xi_t + c^n \eta_t, \tag{3.11}$$

where

$$\zeta_t \sim \text{ iid. } N(0, \sigma^2) \tag{3.12a}$$

$$\epsilon_t \sim \text{ iid. } N(0, (\sigma^r)^2) \tag{3.12b}$$

$$\xi_t \sim \text{ iid. } N(0, (\sigma^\eta)^2) \tag{3.12c}$$

$$\eta_t \sim \text{ iid. } N(0, (\sigma^\eta)^2) \tag{3.12d}$$

and

$$Cov[\zeta_t, \epsilon_t] = Cov[\zeta_t, \xi_t] = Cov[\zeta_t, \eta_t] = Cov[\epsilon_t, \xi_t] = Cov[\epsilon_t, \eta_t] = Cov[\xi_t, \eta_t] = 0$$

Hence, the rational demand from equation (3.9a) results in

$$q_t^r = \beta^r c_{t-1} + \beta^r c^r \tilde{r}_{t-1}^r + \beta^r c^e \tilde{r}_{t-1}^e + \beta^r \zeta_t + \beta^r c^r \epsilon_t + \beta^r c^e \xi_t + \beta^r c^n \eta_t \tag{3.14a}$$

$$q_t^r | F_{t-1} \sim N(\beta^r c_{t-1} + \beta^r c^r \tilde{r}_{t-1}^r + \beta^r c^e \tilde{r}_{t-1}^e, (\beta^r \sigma)^2 + (\beta^r c^r \sigma^r)^2 + [\beta^r \sigma^\eta]^2 [(c^e)^2 + (c^n)^2]). \tag{3.14b}$$

Thus, the rational demand centers on a combination between past rational and emotional believes and accounts for all types of noise in the market: exogenous noise (ζ), rational noise (ϵ), emotional noise (ξ) and noise trader noise (η).

[8]Henceforth, we exclude the hypothetical limit case of a perfect liquid market $\lambda = 0$.

Emotional investors follow their intuition in formulating demands. They simply react proportionally to their current beliefs over returns

$$q_t^e = \beta^e r_t^e, \tag{3.15}$$

where β^e describes the sensitivity of emotional demand to price changes and r_t^e is the emotional perception over log-returns conditional on public information.[9]

According to equation (3.6b), the emotional belief over returns can be formulated as

$$r_t^e = k_{t-1} + k^e \tilde{r}_{t-1}^e + \frac{1}{\sqrt{b}}\zeta_t + \frac{k^e}{\sqrt{a}}\xi_t, \tag{3.16}$$

where ζ_t and ξ_t are distributed according to equations (3.12).

Even if the emotional strategy contains a noise component ξ_t with identical variance as the noise trader noise η_t, it additionally accounts for exogenous shocks and depends on the behavioral information updating parameters a and b

$$q_t^e = \beta^e k_{t-1} + \beta^e k^e \tilde{r}_{t-1}^e + \frac{\beta^e}{\sqrt{b}}\zeta_t + \frac{\beta^e k^e}{\sqrt{a}}\xi_t \tag{3.17a}$$

$$q_t^e | \mathcal{F}_{t-1} \sim N\left(\beta^e k_{t-1} + \beta^e k^e \tilde{r}_{t-1}^e, \frac{(\beta^e \sigma)^2}{b} + \frac{(\beta^e k^e \sigma^\eta)^2}{a}\right). \tag{3.17b}$$

Emotional investors can use differences in past price levels as a proxy for $\tilde{r}_{t-1}^e$.[10] The emotional strategy centers on emotional expectations and accounts only for exogenous and noise trader noise.

Noise traders act randomly

$$q_t^n = r_t^n = \eta_t \tag{3.18a}$$

$$q_t^n | \mathcal{F}_{t-1} \sim N(0, (\sigma^\eta)^2). \tag{3.18b}$$

Therefore, the total order flow issued by investors at date t according to equation (3.8) results in a linear combination of subjective beliefs over log-returns

$$\begin{aligned} Q_t = {} & n^r \beta^r c_{t-1} + n^e \beta^e k_{t-1} + n^r \beta^r c^r \tilde{r}_{t-1}^r + (n^r \beta^r c^e + n^e \beta^e k^e)\tilde{r}_{t-1}^e \\ & + \left(n^r \beta^r + \frac{n^e \beta^e}{\sqrt{b}}\right)\zeta_t + n^r \beta^r c^r \epsilon_t + \left[n^r \beta^r c^e + \frac{n^e \beta^e k^e}{\sqrt{a}}\right]\xi_t + \left[n^r \beta^r c^n + (1 - n^r - n^e)\right]\eta_t. \end{aligned} \tag{3.19}$$

[9]Note that the mathematical equivalence of the rational and emotional strategies, according to equations (3.9a) and (3.15), is not based on a logical similarity in thinking. Rational traders aim the maximization of expected group-profits and their strategy *results* to be proportional to their own current return expectation. Emotional traders simply follow their beliefs over current returns.

[10]Such as a trend-following strategy, as in Farmer (2002). E.g. $\tilde{r}_{t-1}^e = r_{t-1} - r_{t-2} = p_{t-1} - 2p_{t-2} + p_{t-3}$. Thus, they act in accordance with the idea that past prices do encompass enough information in order to provide a basis for investment decisions.

According to equation (3.7), prices are fixed proportionally to the observed total order flow Q_t

$$\begin{aligned} r_t = \frac{c_{t-1}}{2} + \lambda n^e \beta^e k_{t-1} + \frac{c^r}{2}\tilde{r}^r_{t-1} + \left(\frac{c^e}{2} + \lambda n^e \beta^e k^e\right)\tilde{r}^e_{t-1} \\ + \left(\frac{1}{2} + \frac{\lambda n^e \beta^e}{\sqrt{b}}\right)\zeta_t + \frac{c^r}{2}\epsilon_t + \left[\frac{c^e}{2} + \frac{\lambda n^e \beta^e k^e}{\sqrt{a}}\right]\xi_t + \left[\frac{c^n}{2} + \lambda(1 - n^r - n^e)\right]\eta_t. \end{aligned} \tag{3.20}$$

Thus, the log-return represents a linear combination of the subjective return beliefs of each investor type. Moreover, log-returns encompass a fourfold noise pattern, originating from the noise in rational, emotional and noise trader perceptions, as well as from possible exogenous factors.

Equation (3.20) emphasizes the fact that both rational and emotional investors exert influence on prices. While the weight associated with the rational effect $\frac{c^r}{2}$ is constant, the emotional influence exhibits lower values in a more liquid market (i.e. for a higher λ), but remains bounded by the constant $\frac{c^e}{2}$.

When $\lambda n^e \beta^e k^e = -\frac{1}{2}c^e$, the direct impact of the emotional expectation on mean returns disappears, but the emotional strategy continues to affect prices by means of other parameters, such as a, b, k^e and β^e.

Similarly, if rational investors are smart enough in order to infer the current emotional belief, as well as the emotional demand sensitivity to price movements and the emotional constant k^e, they can compensate on average for the existence of emotional traders. Thus, with $c^r \tilde{r}^r_{t-1} = -\left(c^e + 2\lambda n^e \beta^e k^e\right)\tilde{r}^e_{t-1}$, emotional beliefs have no direct influence on the mean of current returns (but the emotional investors maintain their influence through the constant part of the mean return and through the return variance). However, such a situation is economically improbable, given the amount of information the rational investors are assumed to be able to assess.

3.3 Simulations

In this section, we show by means of simulation techniques the evolutionary dynamics of returns and rational and emotional investor wealth who follow the decision rules stated above. The analysis of the wealth evolution in time helps us to draw a final conclusion concerning the survival of the different types of investors.

We simulate 1000 series of $T = 1250$ log-returns r_t according to equation (3.20) (which, assuming that investors decide to buy, hold, or sell only once per day, approximately corresponds to 5 years of trading). We perform a sensitivity analysis by considering different values for the model parameters. Firstly, we fix the proportion of noise traders at $1 - n^r - n^e = 0.05$ and consider three different values for the dimension of the emotional investors' group $n^e \in \{0.25, 0.5, 0.75\}$. Then, we consider the following standard deviations for the different exogenous and endogenous noise components of returns: $\sigma = 0.02$, $\sigma^\epsilon = 0.02$, $\sigma^\eta = 0.03$. In line with the results of Hasbrouck (2005), the inverse market liquidity parameter is taken as $\lambda = 0.08$.

The parameter β^r is derived from equations (3.23) and (3.24) and the emotional demand sensitivity is considered to be in the same order of magnitude: $\beta^e = \beta^r$. Furthermore, the parameters of the information updating processes are set to the following values $c_{t-1} = k_{t-1} = 0$, $c^r = n^r$, $c^e = n^e$, $c^n = 1 - n^r - n^e$, and $k^e = n^e$. The informational weights assessed by emotional investors given the prior and current information can also vary: $a, b \in \{1, 0.01\}$. Following Kyle (1985), we consider the mean rational belief $\tilde{r}^r_{t-1} = -\sum_{s=0}^{t-1} r_s = -p_{t-1}$.[11] The emotional traders are assumed to pursue a trend-following strategy, which reduces to $\tilde{r}^e_{t-1} = r_{t-1} - r_{t-2}$.

We analyze the following cases:

1. Case 1: low proportion of emotional investors active in the market $n^e = 0.25$,
2. Case 2: medium proportion of emotional investors active in the market $n^e = 0.5$,
3. Case 3: high proportion of emotional investors active in the market $n^e = 0.75$.

For each of them, we consider three scenarios:

- ◇ Scenario a: emotional investors weight prior and current information in a balanced way $a = b = 1$,
- ◇ Scenario b: emotional investors underweight prior information $a = 0.01$ and overweight current information $b = 1$,
- ◇ Scenario c: emotional investors overweight prior information $a = 1$ and underweight current information $b = 0.01$.

Using the simulated returns series of equations (3.6a) and (3.6b), we derive the group-specific asset demands q^r_t, q^e_t and q^n_t, according to equations (3.9a), (3.15) and (3.18a), respectively, for each of the cases and scenarios considered.

Subsequently, we focus on group-wealth. At every date t, the wealth is given by the amount of risky asset units held by each investor group ($n^r q^r_t$, $n^e q^e_t$ and $(1 - n^r - n^e)q^n_t$) valuated

[11] Kyle (1985) demonstrates the existence of an unique linear sequential auction equilibrium in a market setting with informed investors and noise traders. The informed investors are the counterpart of our rational traders. They are considered to be able to infer the so called "true" value of the traded asset v_t and to exploit the difference between it and the current price in their strategies. Thus, the rational strategy in our setting corresponds in Kyle's model to $q^r_t = \beta(v_t - p_{t-1})$, where $v_t = p_0 + \epsilon_t$ and $\epsilon_t \sim$ iid. $N(0, (\sigma^\epsilon)^2)$. Given that, according to equation (3.9a) and with $p_0 = 0$, the rational demand is proportional to the rational expectations, this yields to $\tilde{r}^r_{t-1} = E[v_t|\mathcal{F}_{t-1}] - p_{t-1} = p_0 - p_{t-1} = -p_{t-1}$.

according to the change in current price

$$W_t^r = W_{t-1}^r + n^r q_t^r (P_t - P_{t-1}) = W_0^r + n^r \beta^r \sum_{s=1}^{t} r_s^r [\exp(p_s) - \exp(p_{s-1})] \tag{3.21a}$$

$$W_t^e = W_{t-1}^e + n^e q_t^e (P_t - P_{t-1}) = W_0^e + n^e \beta^e \sum_{s=1}^{t} r_s^e [\exp(p_s) - \exp(p_{s-1})] \tag{3.21b}$$

$$\begin{aligned} W_t^n &= W_{t-1}^n + (1 - n^r - n^e) q_t^n (P_t - P_{t-1}) \\ &= W_0^n + (1 - n^r - n^e) \sum_{s=1}^{t} r_s^n [\exp(p_s) - \exp(p_{s-1})], \end{aligned} \tag{3.21c}$$

where $P_t = \exp(p_t)$ represents the current price. It can be derived from current log-returns in virtue of equation (3.20).

3.3.1 Main results

This subsection presents the main results obtained for each case considered in the context of our simulations. We perform one simulation for each case and scenario starting from identical random numbers.

1. Case 1: low proportion of emotional investors active in the market $n^e = 0.25$

   Figures 3.1-3.3 illustrate the log-returns, group-demands and investor group-wealths for each scenario of case 1.

   The simulated returns exhibit similar means for all subcases considered within case 1. However, they become more volatile with the use of adaptive beliefs updating by emotional investors (i.e. under scenarios b and c), especially in case 1c, when emotional investors overweight prior and underweight current information.

   In situation 1a the demand of the emotional is in mean and variance a little bit higher than for the rational group while in cases 1b and 1c, the mean and variance of rational and emotional group-demands are of the same order of magnitude. In all of the subcases (a,b,c) the mean rational group-demand is negative and the mean emotional group-demand positive, which points out that, on average, rational investors sell more, while emotional ones buy more. Group-demands become more volatile under scenarios 1b and 1c.

   The most interesting pattern is shown by group-wealths. When emotional investors overweight current and underweight prior information in forming their beliefs (case 1b), they succeed in gaining more than rational investors during the whole simulated trade period. When emotional information updating develops similar to rational beliefs formation, the rational investors are better off and gain on average (case 1a). Rational investors start earning more from their trades also when the adaptive emotional beliefs formation consists in underweighting current and overweighting prior information but after some time (300 trades) emotional investors reverse the situation earning more for the remaining time (case 1c).

Comparing the results for each scenario of case 1, we observe that the average group-wealths increase for both rational and emotional investors when the emotional information updating is adaptive. The highest mean values are reached under scenario c, at the price of more volatile returns. Thus, if adaptive information updating renders the market to be more unpredictable, it increases in exchange the chances of higher trade profits.

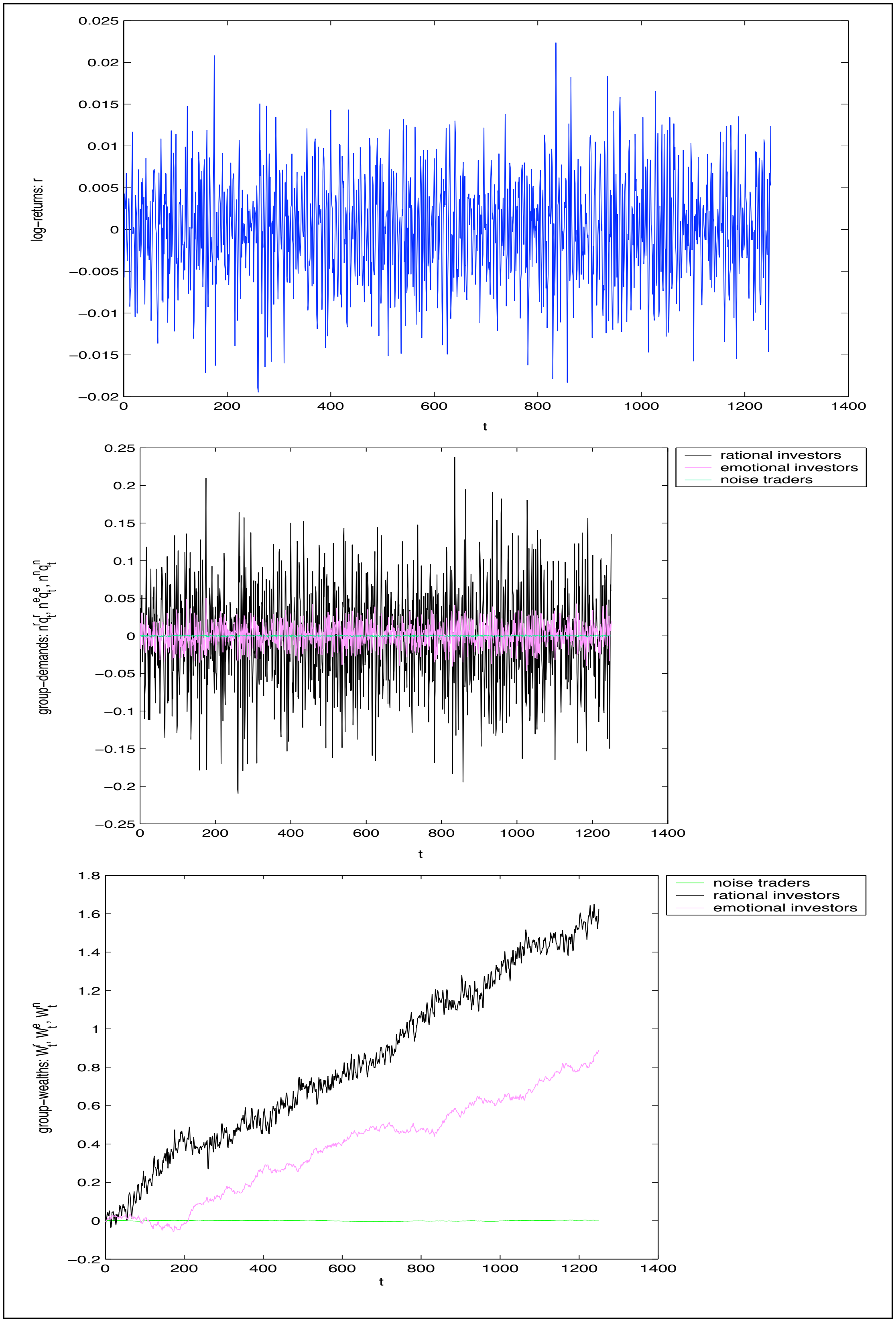


Figure 3.1: Log-returns, group-demands and group-wealths in case 1a: $n^e = 0.25$, $a = b = 1$

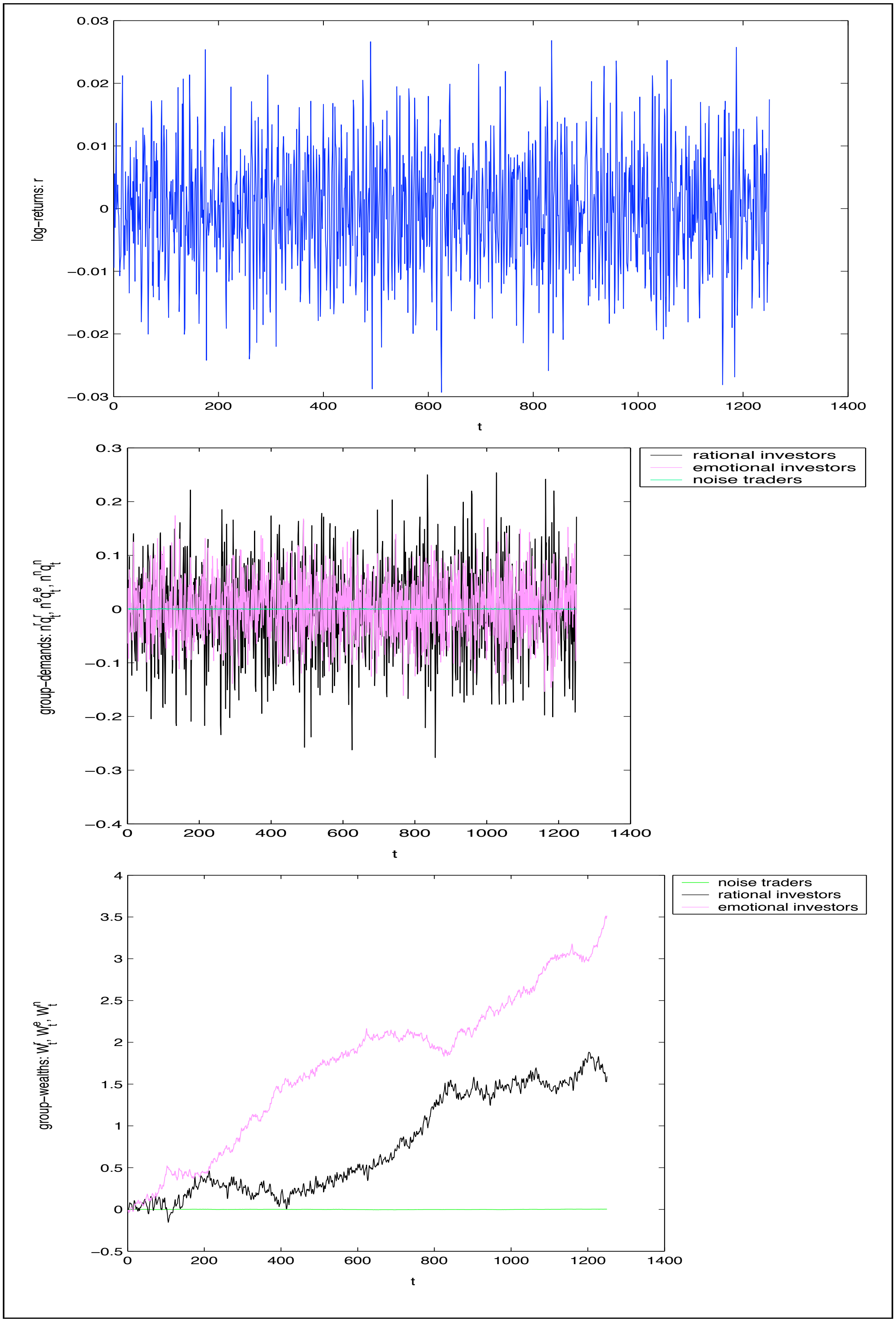


Figure 3.2: Log-returns, group-demands and group-wealths in case 1b: $n^e = 0.25$, $a = 0.01$, $b = 1$

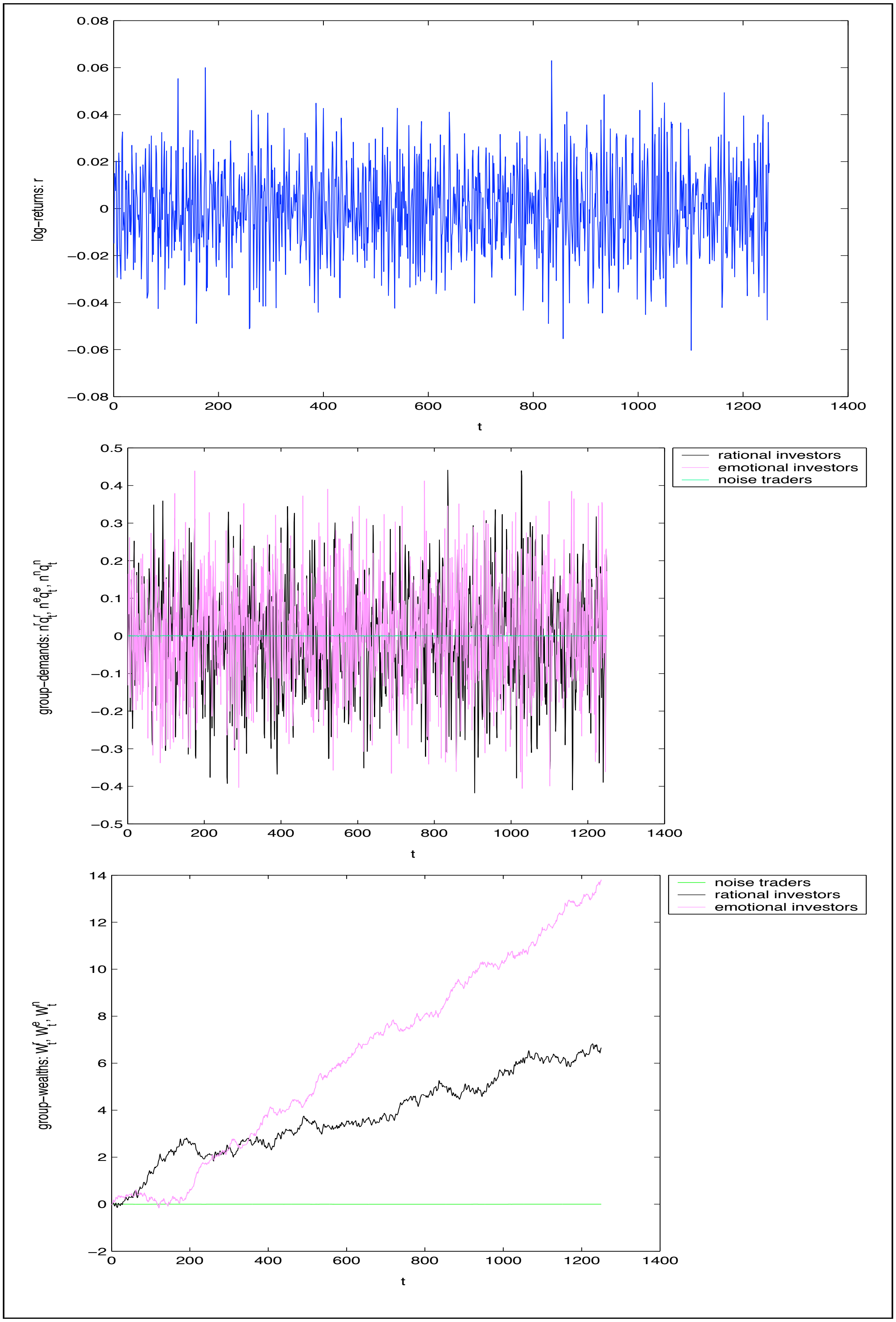


Figure 3.3: Log-returns, group-demands and group-wealths in case 1c: $n^e = 0.25$, $a = 1$, $b = 0.01$

2. Case 2: medium proportion of emotional investors active in the market $n^e = 0.5$

   Simulated log-returns, as well as the demands and wealths of each investor group for all scenarios of case 2 are shown in Figures 3.4-3.6.[12]

   An increase in the proportion of emotional investors (up to values comparable with the proportion of their rational peers) leads to a stronger emotional influence on prices. This increases not only the survival chances of the emotional investors, but also yields an improvement of the general trade benefits, given that average wealth values are always positive and higher for all investor types compared to case 1. However, the market also becomes more volatile. The use of adaptive information updating results in a increased volatility of returns and demands.

   Emotional investors appear again to be the fittest in the market when they actually employ the affective beliefs updating techniques as described in Section 3.2.1 of this chapter, i.e. Only in case 2a and for a quite short period of time rational traders perform better than their emotional peers. In both 2b abd 2c emotional traders beat rational traders during the whole simulated trade period [13] The average group-wealths increase substantially with respect to the benchmark scenario 2a.

   The mean rational and emotional group-demands exhibit further close values of contrary sign for all considered scenarios. In case 2, rational investors always sell on average, while emotional ones always buy. Surprisingly, the rational group-demand appear to be twice as volatile as the emotional one in case 2a, while its variance is always lower for the other two scenarios.

[12] Henceforth, we use different scales for the group-wealths, as a consequence of the fact that wealth values in cases 2 and 3 are much higher on average than in case 1.

[13] Further simulations for different values of the model parameters come to support the finding that such a situation does not represent an accident, but can naturally occur in real market settings.

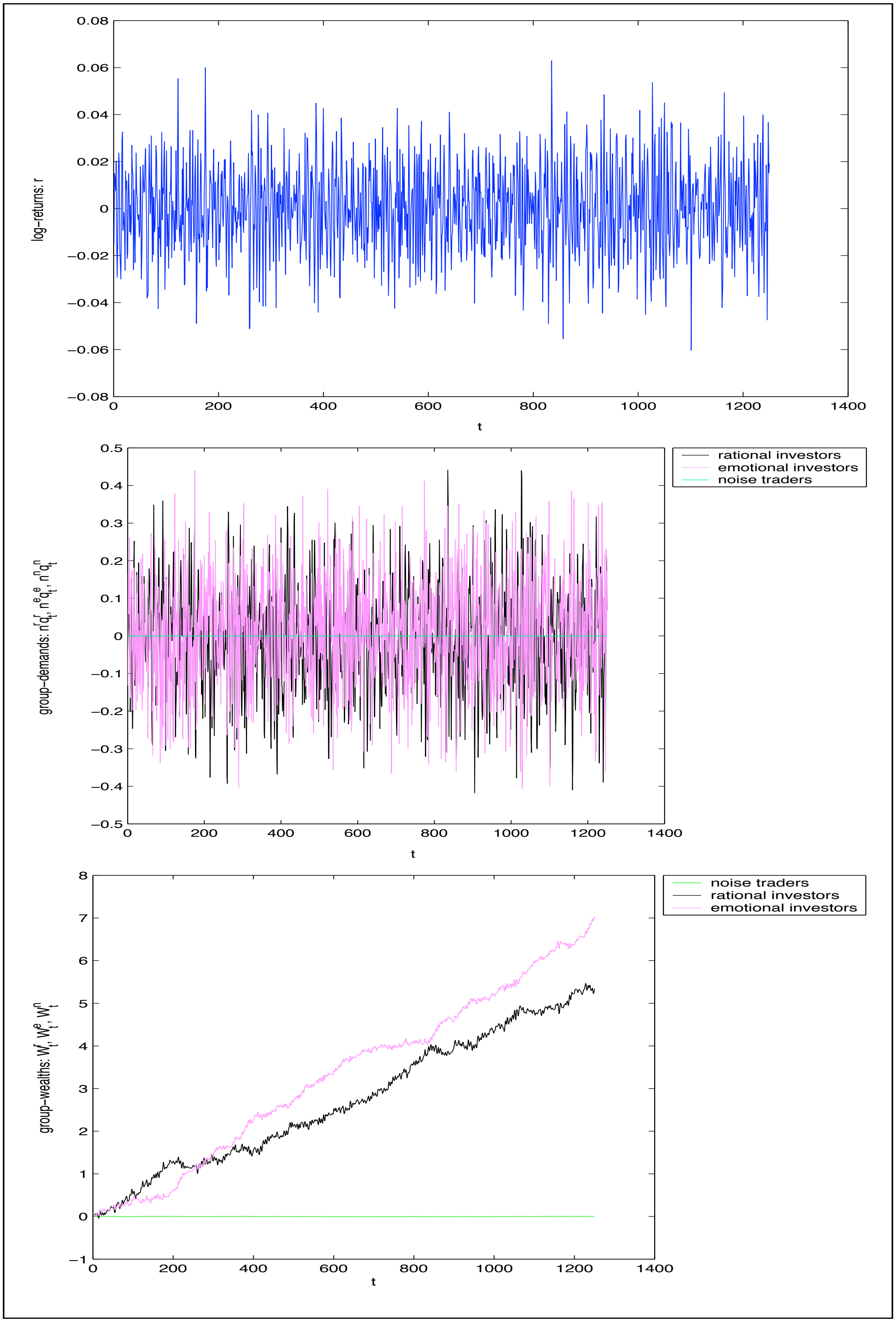


Figure 3.4: Log-returns, group-demands and group-wealths in case 2a: $n^e = 0.5$, $a = b = 1$

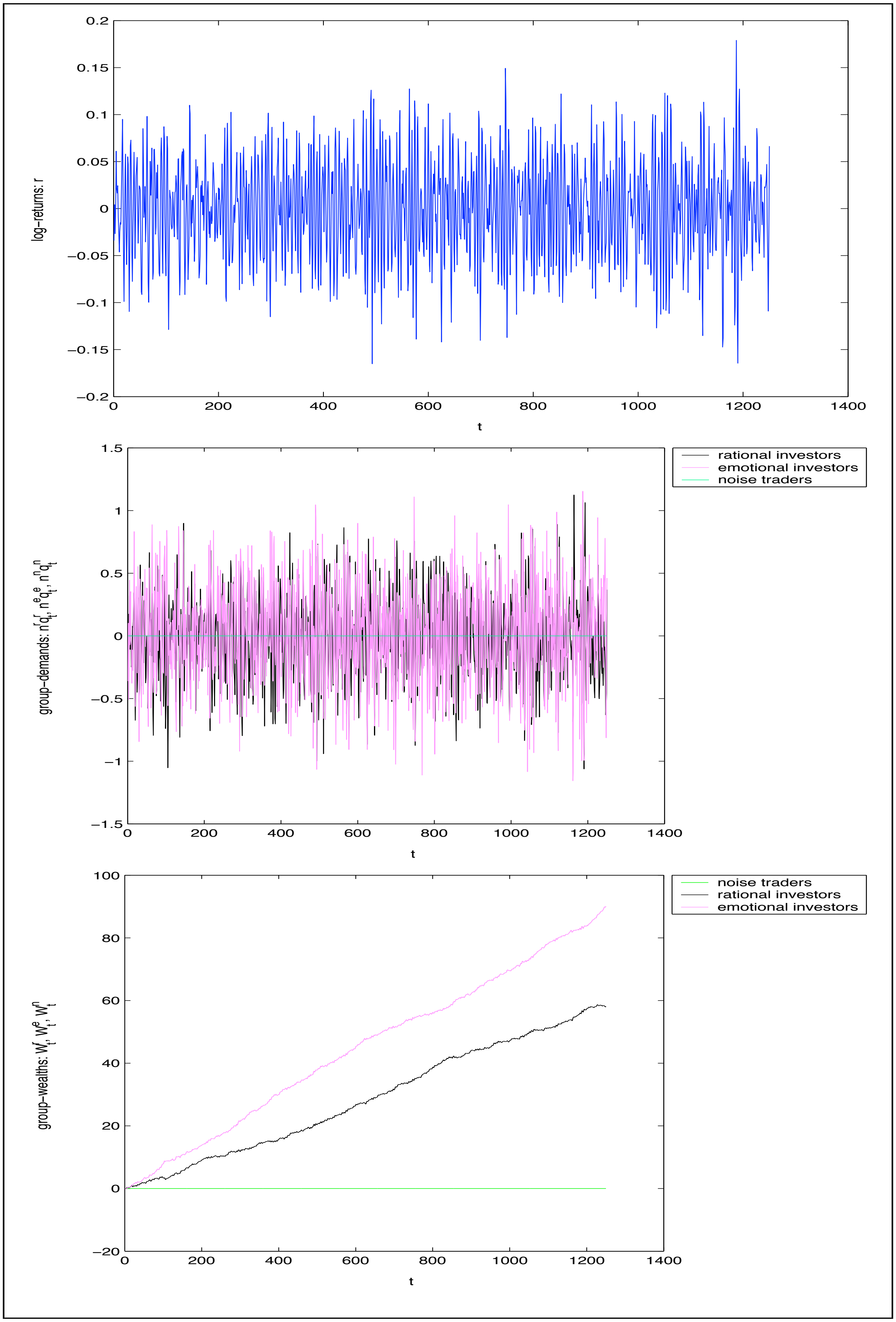


Figure 3.5: Log-returns, group-demands and group-wealths in case 2b: $n^e = 0.50$, $a = 0.01$, $b = 1$

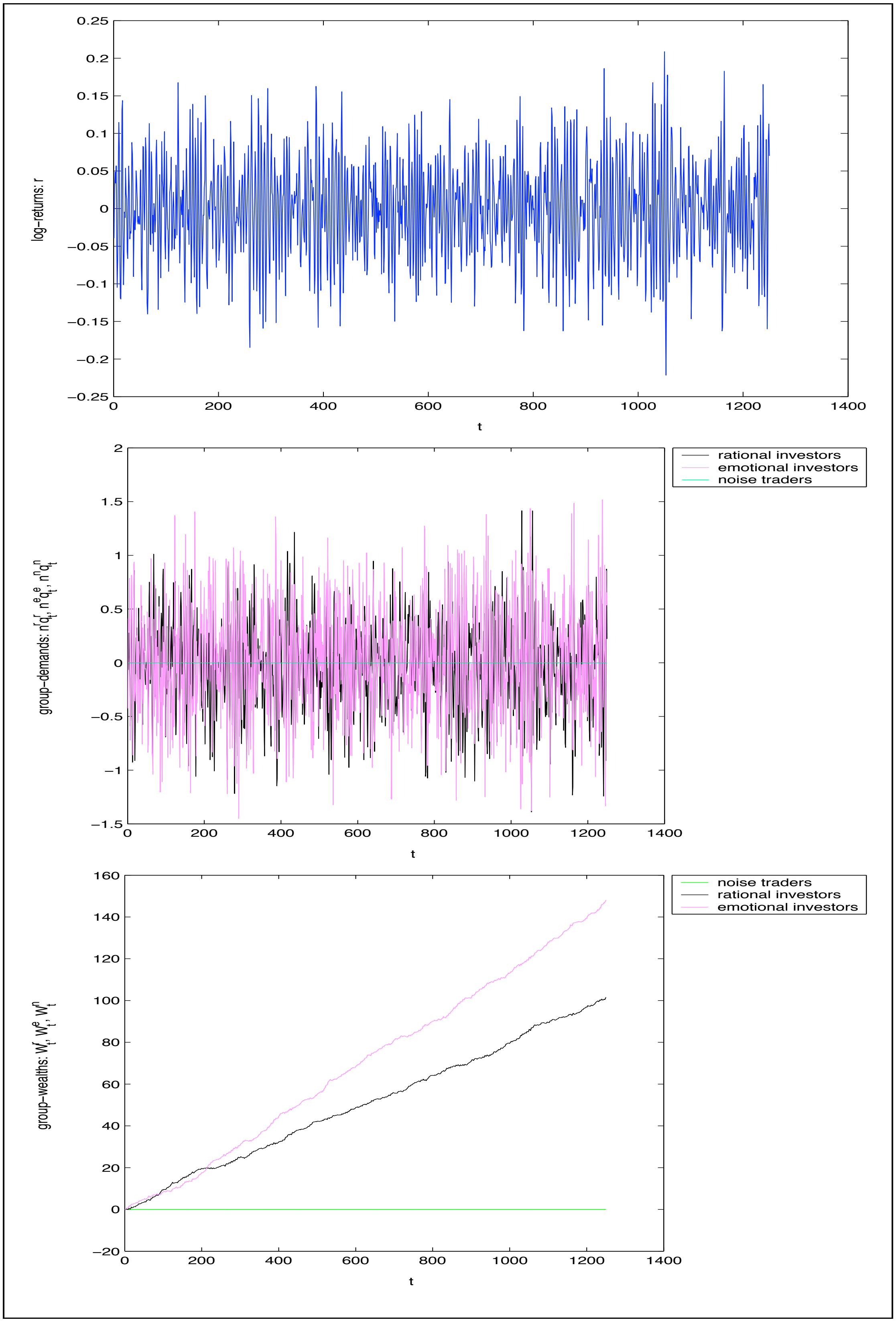


Figure 3.6: Log-returns, group-demands and group-wealths in case 2c: $n^e = 0.50$, $a = 1$, $b = 0.01$

3. Case 3: high proportion of emotional investors active in the market $n^e = 0.75$

   For the considered values of the model parameters, the predominance of emotional investors in the market generates an explosion in prices after approximatively 70 trades. This relies on the high value of the emotional demand sensitivity we employ in our simulations, which, amplified by the high proportion of emotional traders, yields an inflated emotional demand and destabilizes the market. At first sight, an excessively intense emotional activity appears to constitute a threat for a proper market functioning. However, a closer scrutiny of the emotional demand sensitivity to price movements in practice is required in order to draw more precise conclusions in this context.

We have also analyzed the difference between real and subjectively expected group-incomes of rational and emotional investors. The real incomes are calculated at each date t as the product between current demand and changes in real prices, i.e. $n^r q_t^r (P_t - P_{t-1})$ and $n^e q_t^e (P_t - P_{t-1})$, respectively. The subjectively expected incomes rely on subjective rational and emotional beliefs over returns from equations (3.6a) and (3.6b), i.e. $n^r q_t^r (P_t^r - P_{t-1}^r)$ and $n^e q_t^e (P_t^e - P_{t-1}^e)$, respectively. Hence, differences between real and expected periodic incomes originate in the discrepancy between actual market prices and subjective beliefs of the rational and emotional investors $P_t - P_t^r$ and $P_t - P_t^e$, respectively.

We note that, on average, both rational and emotional differences in real and expected incomes, as well as the variances of these differences are small. In cases 1b and 2a rational investors appear to overestimate real prices on average, which yields negative mean discrepancies between real and perceived periodic group-incomes. By contrast, emotional investors overestimate real prices in these cases. We encounter the same situation of overestimation in cases 1a but this time from the emotional investor's part.

3.3.2 Further results

In addition to the main results presented above, we replicate the simulations for a more liquid market, considering $\lambda = 0.001$. While the parameter β^r changes according to equation (3.10), we keep the same values for β^e as in the first series of simulations. With a lower inverse liquidity λ, the rational demand sensitivity β^r increases, which results in an increased rational demand and a higher rational influence on prices. Given that the difference between β^r and β^e is now of two orders of magnitude, rational investors dominate the market.

In general, returns in the more liquid market setting are less volatile and more stable, while group-demands exhibit larger average values than in the less liquid market setting analyzed in Subsection 3.3.1[14]. Moreover, prices do no longer explode when emotional investors are present in large extent in the market (case 3).

In the case of low proportion of emotional traders (Figure 3.7) rational traders perform much more successfully than their emotional peers in all the cases. As soon as the proportion of emotional traders increase (figure 3.8) the use of the affective beliefs updating techniques ensure the preponderance of emotional traders over emotional (middle and lower graphs in figure 3.8). When emotional investors dominate the market (figure 3.9) they will succeed in

[14]Therefore, we use a new scale for the group-demands.

beating their rational peers only under the use of the affective beliefs updating techniques. Moreover, while overweight current and underweight prior information seems to be a win-win strategy from scratch, the reverse strategy takes some time before they can beat their rivals. Interestingly, even when emotional investors dominate the market, their rational peers appear to perform much better when they do not employ the affective beliefs updating technique (i.e. when they weight equally prior and current information).

We report the correspondent group-wealths evolutions for all considered scenarios. In Figures 3.7-3.9. In all these figures, the top panel represent the case with $a = b = 1$, the middle graph the case with $a = 0.01$, $b = 1$, and the bottom graph corresponds to $a = 1$, $b = 0.01$.

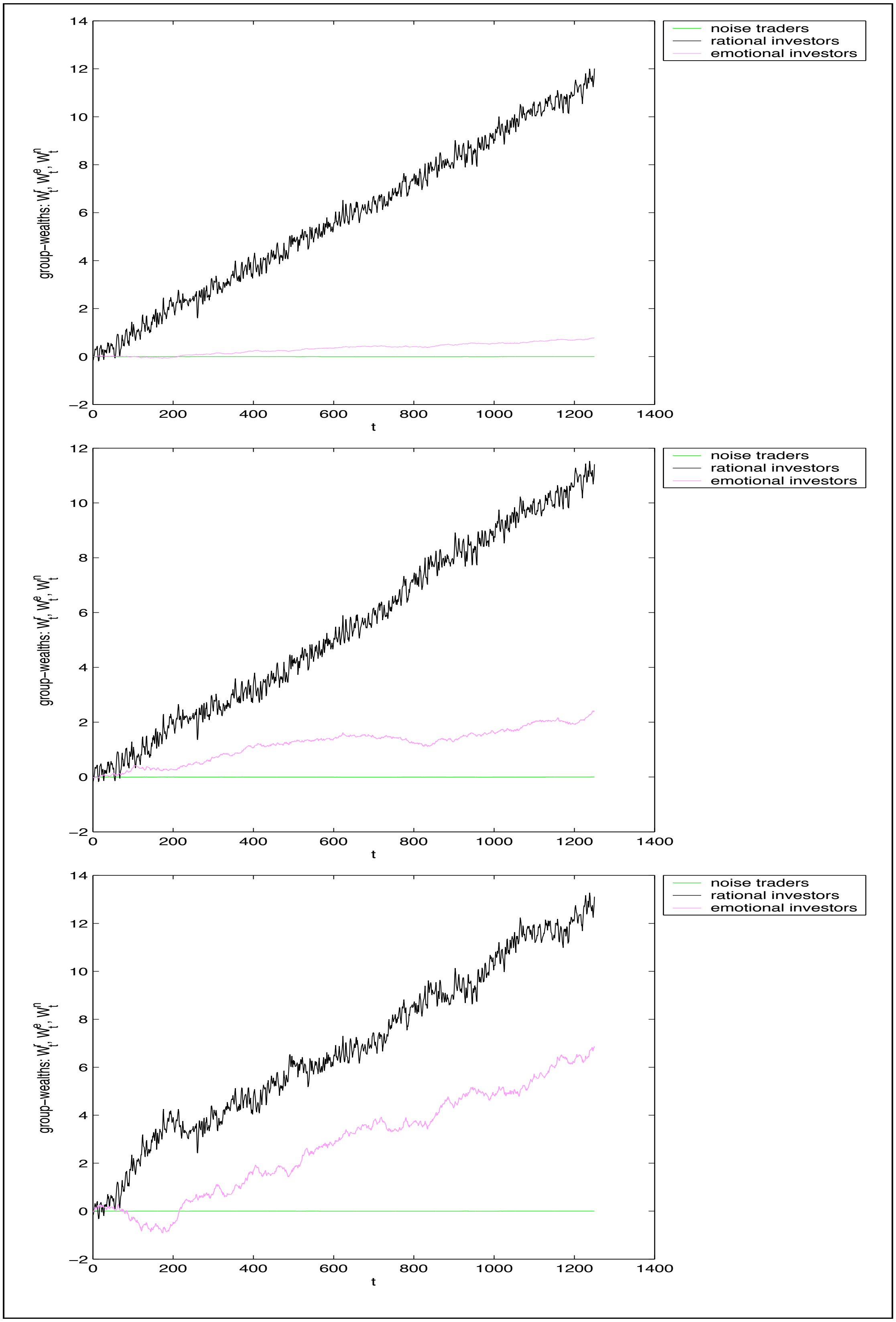


Figure 3.7: Group-wealths in the case $n^e = 0.25$, in a more liquid market: $\lambda = 0.001$

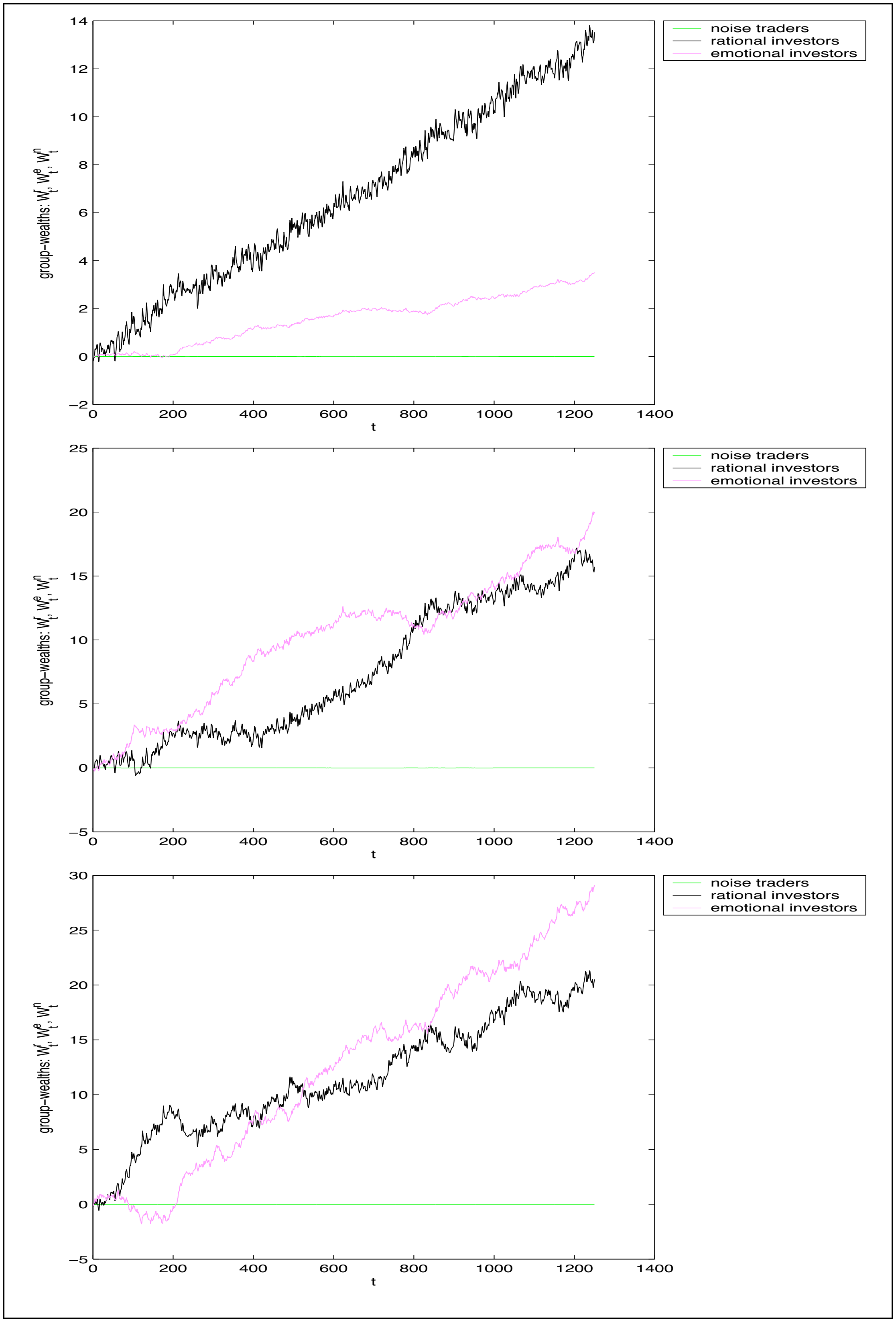


Figure 3.8: group-wealths for $n^e = 0.50$, in a more liquid market: $\lambda = 0.001$

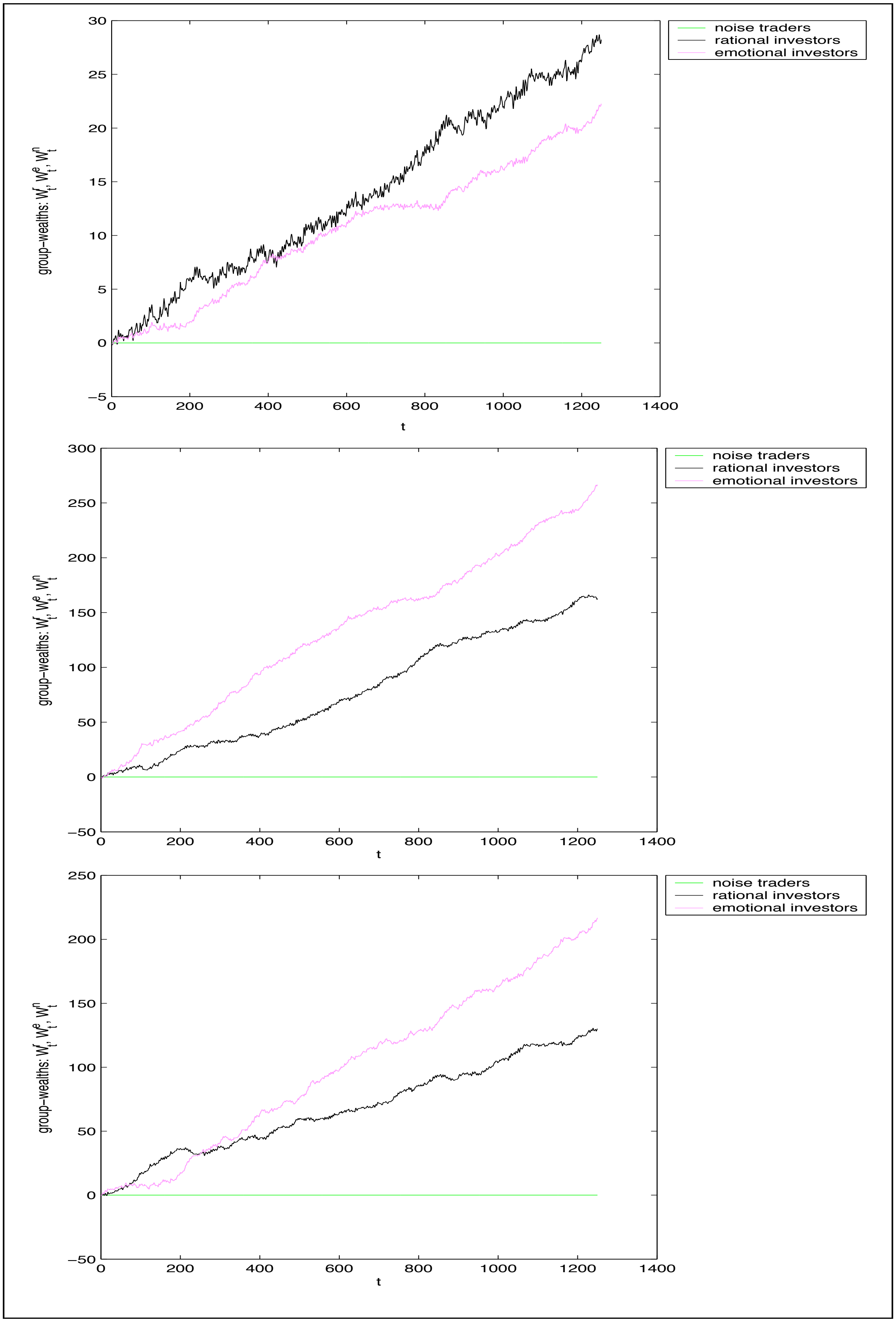


Figure 3.9: Group-wealths for $n^e = 0.75$ in a more liquid market: $\lambda = 0.001$

Subsequently, we try to include in our simulations the fact that, in practice, rational and emotional investors may not be able to sustain high losses for a prolonged period. When one of these two investor types gets out of the market, its group-demand as well as its group-wealth reduce permanently to zero and the market continues to function only with the rest of investors active. We assume that, given the randomness of their demand, noise traders as a group always remain active in the market.

Considering the same parameter values as in the simulations of Subsection 3.3.1, we generate another 1000 simulations of each $T = 1250$ log-returns r_t. We allow as maximum a loss of -5 monetary units and a maximum loss duration of 50 or 100 trades.

The results show that emotional investors get out of the market in cases 1a and 1c. We find this result not very surprising, given that the excessive presence of rational investors in the market (as in case 1) increases their influence on prices and leaves lower survival chances for emotional investors. Moreover, under scenario a, emotional investors do not use an adaptive thinking and their strategy is poorer than that of their rational peers. However, rational investors are also forced out of the market in cases 1b and 2b after after 113 and 75 trades respectively. None of the investor groups runs out of money in case 2c. In case 2a for a maximum duration of loss endurance of 50 trades, emotional investors get out of market after 205 trades being followed by their rational peers after 586 trades.

In short, the simulations emphasize the fact that possible situations (i.e. phases in the market evolution) exist, where emotional investors are better off then the rational ones. Their chances of survival and success increase with the use of affective information updating techniques. Their success appears to be ensured when they overweight current relative to prior information by forming beliefs. This is a clear evidence that, under certain circumstances, emotional investors have high chances of continued existence, which contradicts the traditional conviction that rational traders are the sole survivors.

3.4 Conclusions

This chapter aims to analyze the role of emotions in financial decision making. To this end, we model a market where different types of market participants trade a unique risky asset. These market participants are three distinct investor groups: rational investors, emotional investors and noise traders. We model the formation of individual beliefs, the investor demand strategies, their group-wealths, as well as the price fixation process.

What makes the distinction between the investor types is the way they interpret public information in order to form their subjective beliefs, as well as the strategy they pursue in order to determine the optimal trading volume. Rational investors form their belief by combining past and current information in a traditional Bayesian manner, and maximize the expected group-profits in formulating periodical asset demands. In contrast, emotional investors update information in an adaptive manner, putting different weights on distinct information sources. They also form their demands in an impulsive way by following their own beliefs over returns. Noise traders act randomly.

The formation and revision of beliefs draws upon information interpretation. We focus on the role of emotional investors as a distinct type of traders driven by affect and intuition. We suggest a way to quantify the emotional process of belief revision, showing how emotional investors may balance past information and new evidence in contrast to the traditional updating employed by rational investors.

Beliefs flow into subjective expectations of returns. The demand strategies of the investors are shaped in linear dependence on these subjective returns expectations. We show that the distinct beliefs of different market participants are directly reflected in the informational content of prices.

Furthermore, we test our model by performing numerical simulations for different parameter values and in different market settings. Thus, we examine the evolution of prices, group-demands and group-wealths for various proportions of rational and emotional investors active in the market, as well as for two different values of market liquidity. We also analyze the survival of rational and emotional investors considering a market setting where they cannot sustain high long-lasting losses.

Our results show that there are many situations where emotional investors appear to gain more money than the rational ones. This finding supports the possible survival (and even dominance) of emotional traders in the market, in spite of their apparent simplistic strategy and non-traditionalist revision of beliefs. This contradicts the traditional conviction that only rational investors can survive in the long run. Emotional investors improve their chances of survival with the use of adaptive belief information updating techniques as modeled in this chapter. They appear to be better off when considering new evidence as more important and discarding prior information by belief formation. Similarly, an increase in the proportion of emotional investors active in the market provides long-run benefits not only for themselves as a group, but also for other market participants.

CHAPTER 4

Rational or Emotional Markets? An examination of emotes and cognitive illusions embedded in financial markets

We explore in this chapter the possibility that emotional components in prices trigger cognitive illusions in financial markets which can affect the significance of the informational content of prices.

Treating global markets as a lie detector and taking advantage of the state space models and Markov chains tools, we test if prices contain signs of intentionality which trigger cognitive illusions, and affect investors expectations, confidence and beliefs while making decisions under uncertainty.

4.1 Introduction

For more than thirty years there has been a vigorous debate amongst traders, investors, analysts and fund managers about how financial decisions should be made. In academic circles this debate has led to a discourse about the efficiency, or lack thereof, of financial markets. This chapter aims to address the issue of market efficiency from a novel perspective. The pertinent question we focus on to understand market efficiency is: How emotions interfere with the rationality of the market?

Uncertainty is not only inevitable in economic activity, but magnified in finance because money is based on a trust that is inherently problematic. Money entails claims and credits, so presumes social relations created prospective and therefore unknowable promises.

As we have shown in the introductory chapter of this thesis, rational calculations (i.e the traditional cosequentialist perspective) have been shown to be quite unrealistic as they do not consider the influence of feelings on decision making. Moreover, they can only be retrospective, due to the fact that they cannot go beyond the horizon separating the future from the present. Hence, finance has an inherently emotional component, and the specific emotions in finance arise from the radical uncertainties of money. Since promises are uncertain, reliability, distrust, arousal, and fear, inspire all financial actions.

As we have shown in chapter 2 financial decisions are made in the neocortex region of the brain but when dealing with unusual situations, affect is intervening in the decision process generating certain conflicts between the limbic brain and the neocortex. Moreover sometimes emotional responses to certain phenomena are so strong that the limbic system takes control over the neocortex ruling the decision making process (see Lo and Repin (2001), Arieli et al. (2001) for more references)

In finance uncertainty is labeled as risk, and since uncertainty about claims is always extreme (i.e uncertainty is first perceived by the limbic brain and afterwards in the neocortex), as shown by Loewenstein (2001) decisions rely on future-oriented emotions. Competitive players in financial markets live and die upon predicting future outcomes that are unknowable. No matter how rational are their calculations of past information, they must project emotions and conventions about the unknowable future and through strategies, bring these conjectures back to the present in order to act.

All the strategies made by financial players rely on emotions of trust, distrust, and the expectation or anticipation of credibility, because all these emotions give financial decision makers the feeling of control fostering an esprit de corps when a decision has been made.

The part of the brain that leaps to conclusions based on emotions and feelings is called adaptive unconscious, and the study of this kind of decision making is one of the most important new fields in psychology.

Form a psychological perspective the unconscious is a powerful force but it is fallible, there is a dark side of emotions which comes with the fact that people have a predisposition to fall into cognitive illusions.

One of the most known cognitive illusions which is widely observed in financial decision making is the predisposition of the people to impose order to ambiguous stimuli (Gilovich (1991)). Given this predisposition to detect patterns and make connections, people believe they can extract ordered phenomena in random processes. The problem, however, comes when this tendency is so strong that they may conclude that order exists even when it does not (Kahneman (2003)). People believe that fluctuations in the prices of stocks are far more predictable than what they really are: a random series of changes in stock prices simply does not look random; it seems to contain enough coherence to enable a wily investor to make reliable predictions of future values from past performance.

As shown in chapter 1, the difficulty in accurately interpreting random events can lead market participants to believe things that are not true. Moreover, a random pattern may be quickly explained and integrated into the pre-existing theories and beliefs. These theories serve to bias people's evaluation of new information in such a way that the initial belief becomes solidly entrenched. When this happens, people fall into what is referred to in psychology as *the illusion of validity* (Einhort and Robin (1978)). This states that people often fail to recognize that a particular belief which rests on inadequate evidence is not considered to arise from opinions or values, but a logical conclusion from objective evidence.

A corollary to the illusion of validity is that when examining evidence relevant to a certain belief, people are inclined to see what they expect to see, and conclude what they want to conclude. In other words, information that is consistent with pre-existing beliefs is often accepted at face value, whereas evidence that contradicts them is critically scrutinized and discounted.

Another important cognitive illusion which market players have a preponderation for is the *clustering illusion*. The clustering illusion is a well know phenomena in statistics, whereby people fail to interpret random patterns for what they truly are: random. Instead, they may see many clusters or streaks of similar outcomes and conclude that patterns exist (Gilovich et al (1985) and Gilovich (1991)). One of the most salient characteristics of this cognitive illusion is that it is not eliminated by repeated examination.

Finally, cognitive studies have shown that people often fail to understand what is controllable and what is not. An *illusion of control* (Langer and Roth (1975)) is defined as an expectant probability of personal success which is inappropriately higher than what objective probability would warrant. In other words, the illusion of control is the tendency for human beings to believe they can control or at least influence outcomes which they clearly cannot.

Taking into account these advances in neuroscience, cognitive psychology and behavioral economics we propose a model where we analyze markets as if there were under a 'lie detector' examination.

The 'lie detector' is a type of examination widely use to look for significant involuntary responses going on in a person's body when that person is subjected to stress, such as the stress associated with deception. It does not measure truth-telling; it measures physiological changes triggered by a wide range of emotions. 'Lie detector' examinations are not able to specifically detect if a person is lying but there are certain physiological responses that most of us undergo when attempting to deceive another person.

As we have expressed before, uncertainty in financial markets is an important factor. Moreover, when financial markets exhibit unusual and abnormal prices, people fall into an emotional state prompting them to make affective evaluation (attitudes) that may not conform to the logic of economic rationality in order to deal with trust and distrust triggered by the current state of uncertainty. This affective or emotional reaction can make markets behave at the aggregate level more emotionally than rationally. Thus a 'lie detector examination' can help us to analyze the significance of emotional reactions in prices.

The proposed way to run our emotional test is assuming that the price of a security depends on two components: A *fundamental value*, i.e. the expected present value of all future benefits and costs associated with holding a security, and an *emotional adjustment* which represent the intensity of emotes embedded in prices. Emotes are units of emotion, which quantify emotional reactions. These emotes can become 'lies' to the market in the presence of unusual and abnormal prices triggering certain cognitive illusions. Specifically in our study we concentrate for the sake of simplicity in three types of illusions that can affect the significance of prices: the illusion of validity, the illusion of control, and the clustering illusion.

In order to specify normal, unusual and abnormal prices, we set two lower and upper bounds (time varying due to the clustering illusion) around the emotional adjustment. The emotional adjustment fluctuates around the fundamental price, thus we make the band fluctuate around the fundamental price. Overlapping the fundamental price and its bounds with the observed prices permits to classify the observed prices into normal, unusual and abnormal. A normal observed price is defined as a price that lies between the fundamental price and the first bounds (lower or upper). An unusual observed price is defined as a price that lies between the first and the second bound (lower or upper). An abnormal price is a price that is further away of the second bound (lower or upper).

The fundamental value is modeled as a random walk with constant fluctuations. The emotional adjustment is embedded in the prices producing a series of emotes which mislead investor's sentiment(i.e. how investors form their beliefs), and makes traders more amenable to be influenced by affect. Moreover, when these emotes occur in a short space of time they create a cascade of feelings that develops into an emotional habit forcing traders to desperately find a way to control (illusion of control) and/or find a subjectively convincing explanation(illusion of validity) for what is happening.[1] Assuming that illusions cannot inflate prices forever, the emotional adjustment is a given by a constant plus a martingale sequence. That is, it is a process with constant mean but not necessarily constant fluctuations, due to the *"clustering illusion"* . Also, it is important to notice that, in line with DeBondt and Thaler (1985), and Shefrin and Statman (1994) the impact of negative illusions is higher than the impact of positive ones, this is because investors' tendency to overreact to good and bad news is especially magnified when the news are bad.

We have therefore two unobserved variables, the fundamental price and the emotional adjustment which sets in motion the three afore mentioned types of illusions. The unobserved variables are extracted using a state space model on the observed security price. The fundamental value is a non stationary process, a random walk, driving the trend of the observed prices. The emotional adjustment is given by a constant plus a martingale sequence martingale difference sequence with asymmetric time-varying fluctuations modeled as a GJR-GARCH model - Glosten, Jagannathan and Runkle (1993). The unobserved variables and the parameters are estimated using the Kalman filter and the error prediction decomposition respectively.

The connection between the model with the different types of cognitive illusions is given in the following way. The *clustering illusion*, or notion that traders tend to see clusters in the security returns, is based on studies by Gilovich (1991), Mandelbrot et al (1987), Mandelbroth (2005) and Taleb (2005), and is captured directly by the GJR-GARCH model. Since this type of illusion is embedded in the model, we are accepting *de facto* its existence. Once the model is estimated, we investigate the presence of *the illusion of validity* and the *illusion of control*. The first bound controls for the *the illusion of validity* in the observed prices, that is investors believe that departures from the efficient price show some pattern and try to validate this pattern with a subjective explanation and forecast. When observed prices are above (in absolute value) the second bound investors fall into the *illusion of control*, that is investors overreact, in order to try to control a situation that they clearly cannot. Finally, and in order to be more accurate in the study of emotes and illusions embedded in the prices we perform a study of the transition probabilities between boundaries using Markov chains of orders one,

[1]Subjectively convincing explanation means that the traders convince himself that he understands the situation, which does not implies that the explanation that he found is objectively rational.

two and three. This study shows the probabilities of prices staying within a particular band given which band it belonged to in previous periods.

Our estimations show that for the US markets between 1/01/1980 and 6/17/2004 (6013 observations) there is a 36% chance that prices contain emotional components; In European markets between 1/01/1988 and 6/17/2004 (4263 observations) the probability of emotional components embedded in prices is 50%. Finally in emerging markets between 01/01/1993 and 6/17/2004 (4275 observations) the probability of emotional components is 42%. These interesting results not only shows that emotions should be taken into account, but also help us to a better understanding of price dynamics. Moreover our model provides a rational explanation to the use of "alternative forecasting techniques", like technical analysis, which has been considered by most academics as irrational, but so extensively used by financial players.

The rest of the chapter is organized as follows: Section 4.2 presents the structural model. Section 4.3 briefly presents the data. Section 4.4 shows the empirical results. Section 4.5 concludes and provides an outlook for future research.

4.2 The model

Our intention is to contribute to the existence literature on behavioral finance on the topic that people stop acting rationally and start acting emotionally in presence of unusual and abnormal prices. These illusionary responses bias their judgment, triggering cognitive illusions, which are not eliminated at the aggregate level and are statistically significant in price dynamics. In our model we assume that the price of a security is given by two components: a **fundamental value** which is the expected present value of all future benefits associated with holding a security, and an **emotional adjustment** based on the psychological notion of emote, units of emotion, which under an emotional hijacking trigger cognitive illusions, more specifically the *illusion of validity*, the *illusion of control* and the *clustering illusion*. Therefore the structural model is based on two unobserved components, the fundamental price, denoted by F_t, and the emotional adjustment, denoted by E_t:

$$P_t = F_t + E_t$$

Following the standard financial literature we assume that the fundamental price follows a random walk with constant variance:

$$F_t = F_{t-1} + u_t,$$

where u_t is a Gaussian *i.i.d.* random variables with zero mean and constant variance. That is $u_t \sim \mathcal{N}(0,1)^2$.

The emotional component, however, is a stationary process, given the fact that emotions cannot drive prices forever. Furthermore, emotions are always present but they tend to change over time and evolve around the fundamental price. When the emotional load is strong, the observed price will depart from the fundamental price. After some period, emotions become

[2] We explain later on why we have chosen the variance to be 1 and not some constant σ^2

weaker and the observed price approaches the fundamental price. This pattern is constantly repeated creating oscillations around the fundamental price, which are stationary. However, weak emotional loads tend to be followed by weak emotional load, and viceversa. Consequently, the observed prices show volatility clustering, which in terms of the structural model implies time varying fluctuations in the emotional component. That is

$$E_t \sim \mathcal{N}(0, \sigma_t^2)$$

where σ_t^2 follows a GJR-GARCH type model

$$\sigma_t^2 = \omega + \alpha E_{t-1}^2 + \gamma E_{t-1}^2 d_{t-1} + \beta \sigma_{t-1}^2 \tag{4.1}$$

where $d_{t-1} = 1$ if $E_{t-1} < 0$. This explains why the variance of u_t is fixed to a constant. We may substitute the equation of the efficient price into the equation of observed price yielding $P_t = F_{t-1} + \varepsilon_t$ where $\varepsilon_t = u_t + E_t$ is an error term with mean zero and variance $1 + \omega + \alpha E_{t-1}^2 + \gamma E_{t-1}^2 d_{t-1} + \beta \sigma_{t-1}^2$. If the variance of u_t would be another parameter, say ρ, instead of 1, it would not be identified because the model would be estimating $\rho + \omega$ as a single parameter and hence it would be impossible to disentangle ρ and ω from the estimate.

In our model, positive past emotions ($E_{t-1} > 0$), and negative past ones ($E_{t-1} < 0$), have different effects on the conditional variance. Positive emotions have an impact of α, while negative emotions have an impact of $\alpha + \gamma$. Thus, if $\gamma > 0$ then the effect of the negative emotions is magnified by an increase in the volatility.

In short, the structural model consists of two unobserved components. The fundamental price that follows a random walk, and the emotional adjustment that is stationary with GARCH effects, leading to a linear state space representation. Parameters, fundamental prices and the emotional components are estimated using the Kalman filter and maximum likelihood using the error prediction decomposition.[3]

4.2.1 Emotions and their impact on prices

Our aim is to study how the emotional responses to unusual data flows into three different types of illusions embedded in security prices: clustering, validity and control. The first one is inherent in our model due to the use of the GJR-GARCH. That is, we assume *a priori* its existence. This assumption does not present, in our opinion, a problem given that clustering in financial returns is one of the most well known phenomena. The illusions of validity and control are the most important objects of our study and their existence is not assumed, but they may be detected once the model is estimated.

The *illusion of validity* can be present in financial markets due to the psychological phenomenon of denial, which refers to the discomfort felt at a discrepancy between what individuals already know or believe, and new information. It therefore occurs when there is a need to accommodate new ideas or situations. Denial in general has a close link with learning from experience. If someone is called upon to learn something which contradicts what he already thinks he knows, particularly if he is committed to that prior knowledge, he is likely to resist the

[3]Because of the presence of GARCH effects in the emotional adjustment, the standard Kalman filter does not apply. Instead we follow Harvey, Ruiz and Sentana (1992).

new learning. Learning from our own mistakes is in general something difficult, uncomfortable, or even humiliating. This is why people are not likely to admit that the content of what has been learned is not valuable. To do so would be to admit that one has been fooled. Therefore denial appears when the observed price deviates significantly from what traders believed was going to happen. This belief, given our model, is the efficient price. An unusual departure of the observed price from the efficient price may cause denial, triggering the illusion of validity. In other words, if the observed prices have a normal behavior, that is around the efficient price, traders confirm their beliefs. However, if observed prices show an unusual departure from their normal trajectory, traders experience denial trying to fit a pattern to this unusual behavior. Unusual observed prices are defined as the prices that are away from the efficient price between one and two times the standard deviations of the emotional adjustment. That is, a normal price evolves within the bands $F_t \pm \sigma_t$ and a unusual price evolves between this band and $F_t \pm 2\sigma_t$, as shown in Figure 4.1(where σ_t is assumed constant for convenience).

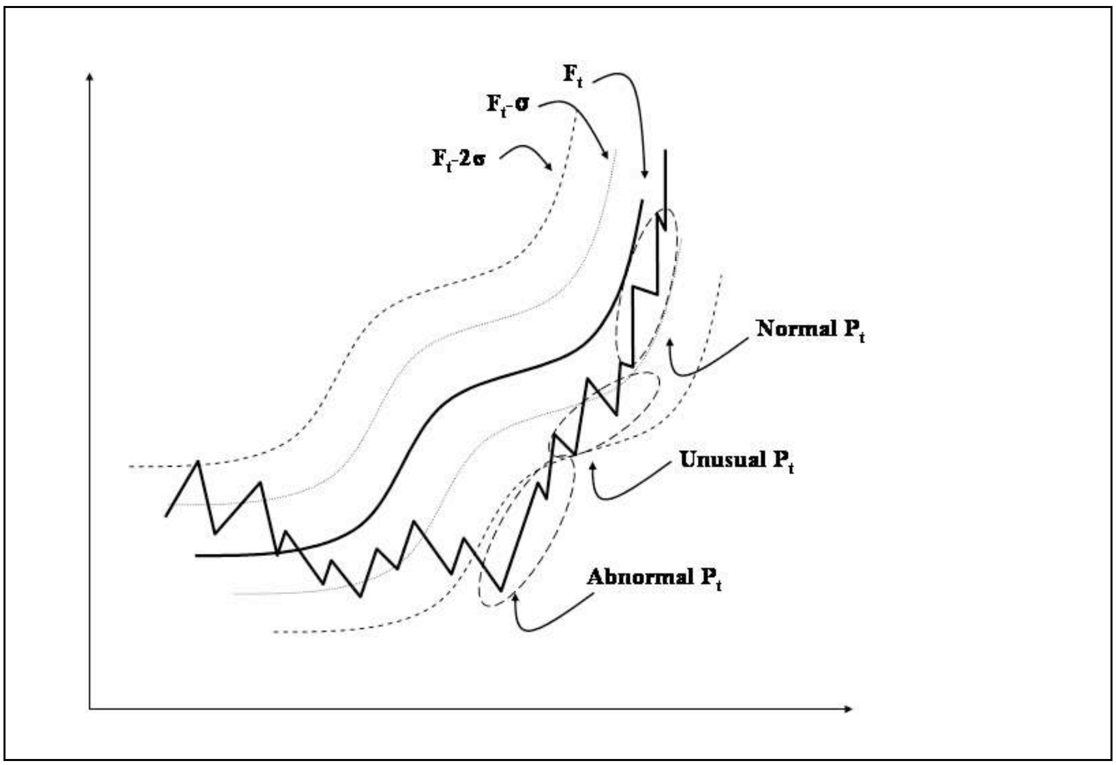


Figure 4.1: Efficient price, illusion's boundaries and observed prices

The *illusion of control* is the accurate way of understanding overreaction in financial markets. This is triggered by an excessive optimism or pessimism that causes prices to be driven too high or too low from their fundamental values. According to DeBondt and Thaler (1985) it is now well established that Bayes rule is not an apt characterization of how individuals actually respond to new information. Moreover as sustained by Kahneman, Slovic, and Tversky

(1982), in revising their beliefs, individuals tend to overweight recent information and underweight prior information. People seem to make predictions according to a matching rule which states that the predicted value is selected so that the standing of the case in the distribution of outcomes matches its standings in the distribution of impressions. Therefore, overreaction appears when the observed price deviates abnormally from what the traders believe is going to happen. An abnormal departure of the observed price from the efficient price may cause overreaction, hence triggering the illusion of control. We define an abnormal observed price to be a price that is away from the efficient price by more than two times the standard deviation of the emotional adjustment. That means an abnormal observed price evolves beyond the boundary $F_t \pm 2\sigma_t$, as shown in Figure 4.1.

The choices of one and two times the standard deviation of the emotional adjustment is subjective. Nonetheless it is based in Bartov and Mohamram (2004), and Carhart's(1997) methodologies to estimate abnormal returns which have been widely accepted in the corporate finance literature.

Finally, as illustrated in Figure 4.2. In a Gaussian density, the probability mass within $\pm\sigma$ around the mean is 68.26%. From $\pm\sigma$ to $\pm 2\sigma$ it is 27.19% and further away of $\pm 2\sigma$ it equals 4.55% of the probability mass. Thus, if a random variable is Gaussian distributed, 68.26% of the realized values will be, in some sense, close enough to the expected value, the mean. However, 27.19% of the realized values are not close to the expected value, but neither absolutely far from it. They are somehow unusual. Finally 4.55% of the realized values are far or very far. That is, as the last interval is unbounded (it goes from $\pm 2\sigma$ to $\pm\infty$) there is a likelihood of 4.55% of finding an extreme observation that we denote as abnormal.

4.2.2 Are illusions self-perpetuated?

Psychological research showed that illusions are not eliminated by repeated examination (Piattelli-Palmarini 1996)). Thus, it is an interesting issue to study the probability that prices remain in an emotional/normal region given that they have exhibited a past normal, unusual or abnormal behavior. This is done using Markov chains. In order to define the chain two aspects are involved: the number of states and the order of the chain.

The number of states is the number of possible states in which the observed price can lie. So far we have defined three possible states: normal, unusual and abnormal; denoted as {N,U,A}. A more refined classification is possible by differentiating between positive and negative unusual and abnormal prices. The Markov chain will then have 5 states that we denote $\{\mathrm{N},\mathrm{U}_+,\mathrm{U}_-,\mathrm{A}_+,\mathrm{A}_-\}$. Behind these 5 states lies the asymmetry between positive and negative influence of emotions triggered by the cognitive illusions. Due to the fact that the econometric model accounts for positive and negative effects on emotions, we expect these emotes to be different.[4]

The second aspect of the Markov chain is its order. The order basically refers to the number of past periods that we are conditioning on. A Markov chain of order d specifies the current

[4]Please notice that a normal state, N, is equivalent to an observed price which does not incorporates illusions. A positive (negative) unusual state, U_+ (U_-), is equivalent to an observed price containing an optimistic (pessimistic) illusion of validity. A positive (negative) abnormal state, A_+ (A_-), is equivalent to an observed price containing an optimistic (pessimistic) illusion of control.

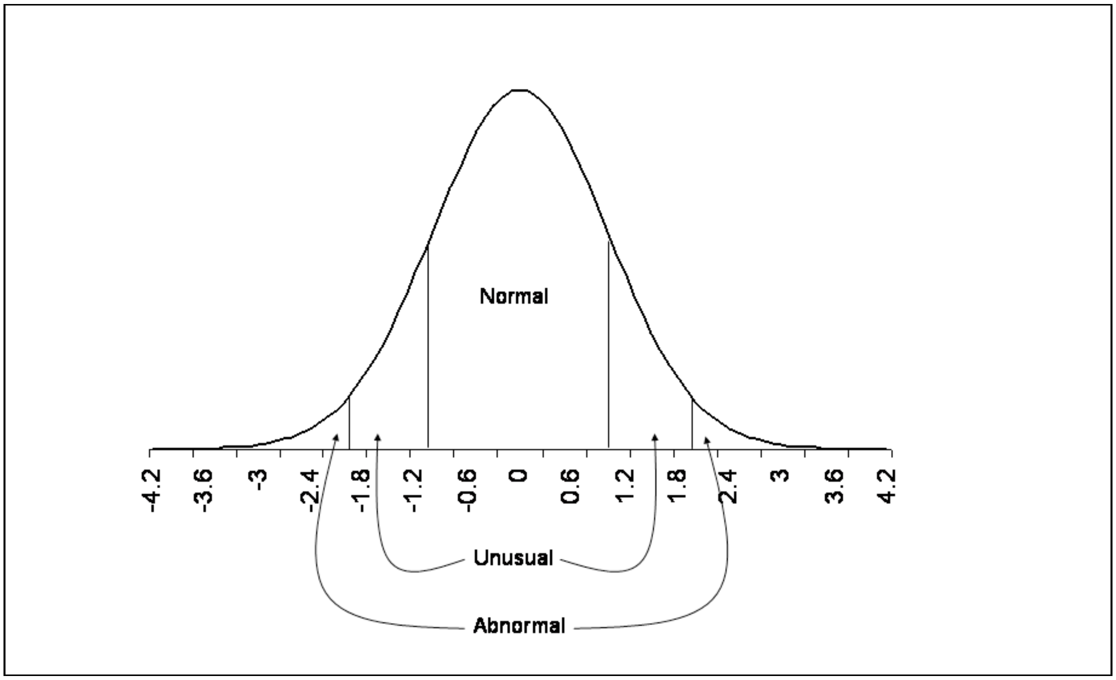


Figure 4.2: Gaussian pfd and probability mass within the boundaries

state of the observed price conditional to the states of the price in the last d periods. For example, a chain of order one means that the state of the observed price at time t is dependent on the state at time $t-1$. A chain of order two is dependent on the state of the observed price in the last two periods, $t-1$ and $t-2$, and so forth.

A Markov chain, regardless of the order and the number of states, is completely characterized by transition probabilities. For example, for a chain of order one the transition probability is defined as the probability that the observed price is in state k at time t given that it had been in state j at time $t-1$. This probability is denoted as P_{jk}. If the chain is of order two, we add the dependence of the probability on the state of the price in $t-2$: that is, P_{rjk}, which denotes the probability that the observed price is in state k at time t and in state j at time $t-1$ given that it had been in state r in time $t-2$.

For example, if the observed price may be in the states {N,U,A} and the chain is of order one, the transition probabilities are written as a 3×3 matrix

$$\begin{pmatrix} P_{NN} & P_{NU} & P_{NA} \\ P_{UN} & P_{UU} & P_{UA} \\ P_{AN} & P_{AU} & P_{AA} \end{pmatrix}$$

where, for instance, the cell P_{NN} is the probability that the observed price at time t has no emotional adjustment given that at time $t-1$ there were no emotional component, whilst the cell P_{UA} is the probability that the observed price triggers the illusions of control given that in $t-1$ there was an illusion of validity.

The maximum likelihood estimators (MLE) of these probabilities are the empirical probabilities. For a chain of order one, the MLE of P_{jk} is given by

$$\hat{P}_{jk} = \frac{n_{jk}}{\sum_{k=1}^{K} n_{jk}} \tag{4.2}$$

where K is the number of states and $n_{jk} = \sum_{t=1}^{T} \mathbb{I}_{\{k\}}(t)\mathbb{I}_{\{j\}}(t-1)$ and $\mathbb{I}_{\{k\}}(t)$ is an indicator function that takes the value 1 if at time t the observed price is at state k. Similarly for $\mathbb{I}_{\{j\}}(t-1)$. The MLE estimator for P_{rjk} is

$$\hat{P}_{rjk} = \frac{n_{rjk}}{\sum_{k=1}^{K} n_{rjk}} \tag{4.3}$$

where $n_{jk} = \sum_{t=1}^{T} \mathbb{I}_{\{k\}}(t)\mathbb{I}_{\{j\}}(t-1)\mathbb{I}_{\{r\}}(t-2)$, and similarly for higher orders of the chain.

We consider Markov chains with three and five states, {N,U,A} and {N,U_+,U_-,A_+,A_-} respectively. Regarding the order of the chain, because illusions are not eliminated by repeated examination, we consider orders 1, 2 and 3. We will estimate matrices of transition probabilities $\hat{P}_{jk}$, $\hat{P}_{rjk}$ and $\hat{P}_{zrjk}$ for z, r, j, k corresponding to {N,U,A} and {N,U_+,U_-,A_+,A_-}.[5]

4.3 Data

In order to study cognitive illusions embedded in financial markets, we test our model with data from the US, Europe and emerging markets through markets indexes. The chosen index is the MSCI or Morgan Stanley Composite Index, which is widely used as a benchmark, especially in Europe.

The MSCI Europe Index is a free float-adjusted market capitalization index that is designed to measure developed market equity performance in Europe. The MSCI Europe Index consists of the following 16 developed market country indices: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom

The MSCI US equity index includes equity securities of US domiciled companies traded on the NYSE, AMEX, and the NASDAQ, except investment trusts (other than REITS), mutual funds, equity derivatives, limited partnerships, limited liability companies and business trusts that are structured to be taxed as limited partnerships, and royalty trusts. The MSCI US defines the large cap index as consisting of the 300 largest companies by full market capitalization in the investable market segment, the Mid Cap Index as comprising the next 450 companies, and the Small Cap Index as consisting of the remaining 1,750 companies.

The MSCI Emerging Markets Index is a free float-adjusted market capitalization index that is designed to measure equity market performance in the global emerging markets. The

[5] In theory we could consider higher orders. However, in practice to handle more than three orders is quite problematic given that the dimension of the matrices increases exponentially. For example, the transition probability matrix of order four, for five states, is of dimension 5×625.

MSCI Emerging Markets Index consist of the following 26 emerging market country indices: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, Turkey and Venezuela.

We use daily data obtained from a Reuters terminal. For emerging markets (EM hereafter) and Europe (EU) between 1/01/1988 and 6/17/2004 (6013 observations) and for the US market between 1/01/1980 and 6/17/2004 (8935 observations). We have deleted all the zeros which correspond to non trading days present in the sample, yielding 4275, 4263 and 6013 observation for EM, EU and US respectively.

Figure 4.3 shows the sequence of prices. Some features of the observed data are: The Internet boom is much more present in the European and USA markets. The increase in prices and volatility in the second third of the sample is much more remarkable for EU and USA than for EM.

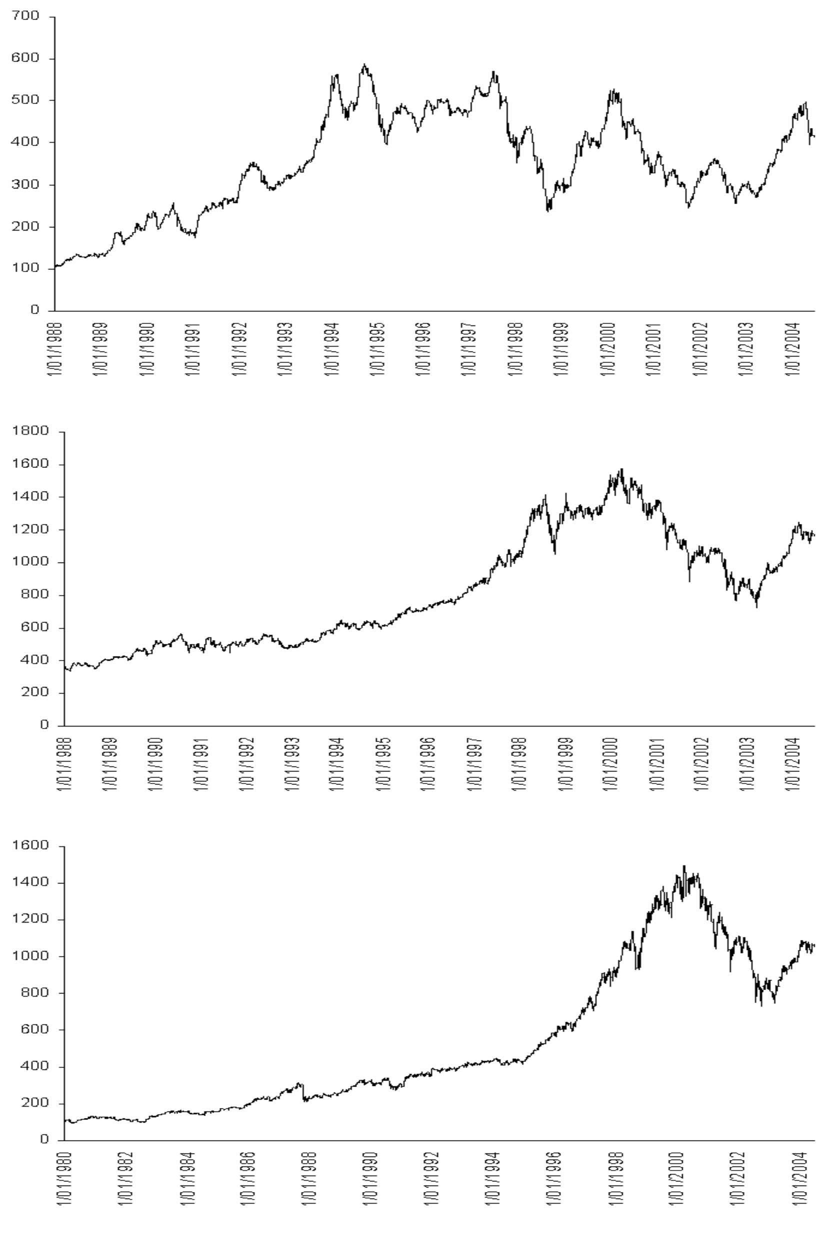
4.4 Results

Figures 4.4, 4.6 and 4.8 show the observed prices, the estimated fundamental price and the boundaries. The top plot shows the whole sample and the bottom plots are zooms at different periods, one quiet and two very volatile. In general the fundamental price follows the trend of the observed price, although the former is smoother than the latter. In periods of high volatility departures of the observed prices from the fundamental prices are higher. In the first left panel of each figure we can see that in quiet periods, like the beginning of the sample, the two processes dovetail nicely and the variance is very small. However, in a period of high volatility the boundaries widen because of the clustering of illusions. When the observed price departs from the fundamental price, our interpretation implies that the observed price progressively includes more and more illusions, despite the widening of the boundaries. During the first days of departure the observed price includes illusions of validity, that is it falls within the two first boundaries. If the departure does not go further the price tends to come back to the fundamental price. If, by contrast, the difference between the two prices increases traders still try to gain control over the pattern falling in the illusion of control, which makes prices to deviate much more from the fundamental price and so widening the boundaries.

Table 4.1 shows the estimation results of the model. All the parameters are significant, meaning a strong dynamical pattern in the volatility of the emotional adjustment. The parameter that measures the asymmetry of the volatility is positive and significant in all cases, meaning that negative emotions cause more volatility than positive ones.

Table 4.2 shows the probabilities of being in abnormal, unusual or normal state. Our results show that in the US markets there is a probability of 36.2% that prices contain emotional components. In European markets the probability of emotional components embedded in prices, is much higher, 50.2%. Finally in emerging markets the probability of emotional components is 42.2%. Among the percentages of observations with illusions, clearly there are more illusions of validity than of control.

Tables 4.3-4.7 show all the transition probabilities. Odd tables show the transition probabilities of Markov chains with three states, {N,U,A}, for orders one, two and three respectively. Even tables show the transition probabilities for Markov chains with five states



From top to bottom, EM, EU and US MSCI indexes.

Figure 4.3: Observed prices.

$\{N, U_+, U_-, A_+, A_-\}$ and orders one and two.

From the odd tables we conclude that the probability of remaining in one state (given by the cells $P_{N,N}$, $P_{U,U}$, $P_{A,A}$ in Table 4.3, $P_{N,NN}$, $P_{U,UU}$, $P_{A,AA}$ in Table 4.5 and $P_{N,NNN}$, $P_{U,UUU}$, $P_{A,AAA}$ in Table 4.7) is higher than any other probability. The highest probabilities are those of being in a non emotional state. However, if we enter into an emotional state, more specificality into an emotional hijacking triggered by the illusion of control, it is more likely that we remain in that state than the if we fall into an emotional state driven by the illusion of validity. That is $P_{A,A}$, $P_{A,AA}$ and $P_{A,AAA}$ are higher than $P_{U,U}$, $P_{U,UU}$ and $P_{U,UUU}$.

As previously mentioned, the clustering of illusions increases in a period when the observed price departs from the fundamental price more. But, at the same time, the observed price tends to incorporate more and more the other two illusions. In fact, what the tables tell us is that if from t to $t+1$ the price has incorporated an illusion of control, there is a higher probability to remain under an illusion of control than to revert to the fundamental price. For example in Table 4.5, if we start in $t-2$ at N or U and we move in t to A, in $t+1$ the state with the higher probability is A as well. Or in Table 4.7, if we start in $t-3$ in N or U and we move to A in $t-2$, the states with the higher probability for the next two periods are both A.

If we start in a period triggered by an illusion of control and in the next period the observed price either includes illusions of validity or nothing, then it is very likely that the observed price will tend towards the efficient price. For example, in Table 4.7 if in $t-3$ observed prices contained illusions of control and in $t-2$ they contained illusions of validity or no illusions, the higher probabilities from $t-1$ to t are to stay close to the fundamental price. In other words, if in $t-3$ the state was A and in the $t-2$ it was U or N, the higher probabilities are $P_{A,NNN}$ and $P_{A,UNN}$ respectively for periods $t-1$ and t for EM and USA markets and $P_{A,NNN}$ and $P_{A,UUU}$ for EU market.

Let us now take a look to the even tables. As in the other tables, the higher probabilities are ones of staying in the same state all the time. However, despite the previous results, there is a very interesting phenomenon. The probability of observing a price with positive emotions driven by the illusions of validity for several periods is higher than the probability of observing a price containing negative emotions driven by illusions of validity for several periods. But the probability of observing, for several periods as well, a price with positive emotions driven by the illusion of control is higher than the probability of observing a price with negative emotions driven by the illusion of control. For example, looking at Table 4.6 we see that $P_{U_+,U_+U_+} < P_{U_-,U_-U_-}$ but $P_{A_+,A_+A_+} > P_{A_-,A_-A_-}$. It basically means that when the observed price contains positive emotions (illusions of validity), traders spend less time examining, looking for a pattern, and we fail into the illusion of control earlier than if the illusions were negative. This confirms the idea, that traders do not validate long enough in the presence of good news and they enter into the illusion of control quicker then if news were bad.

We also see from the tables that the probability of jumping more than two states in one period is very small. For example, if the observed price does not contain emotional components, the probability that the day after will be driven by the illusion of control is very small.

Overall, the US market index has less illusionary components of validity and control, though it has a stronger clustering illusion component. The reason for the latter is the increase in the fluctuations during the internet boom. A plausible reason for the former is that the US market is more advanced, mature and rational than the other markets.

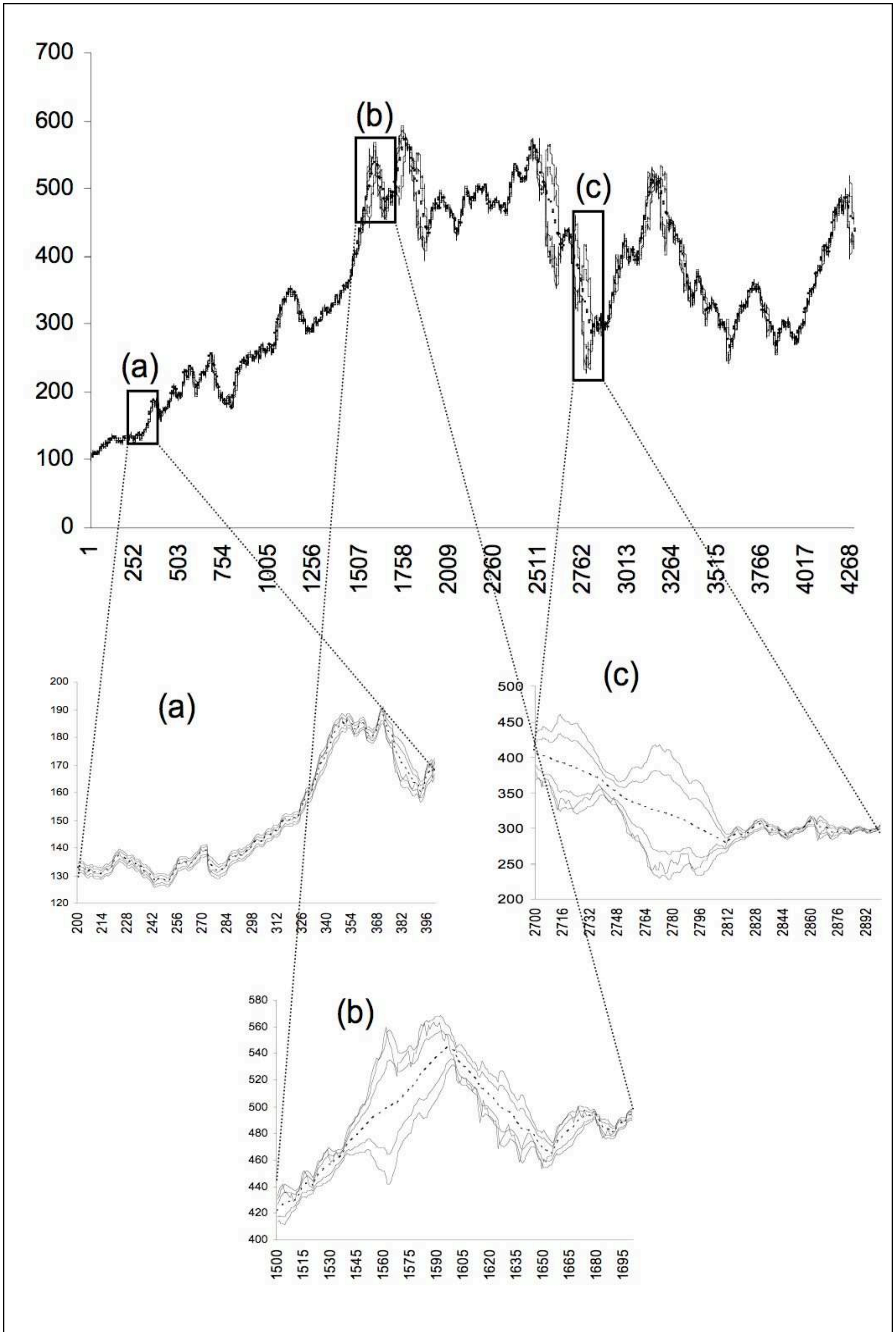


Figure 4.4: Observed prices, estimated fundamental prices and boundaries. EM data.

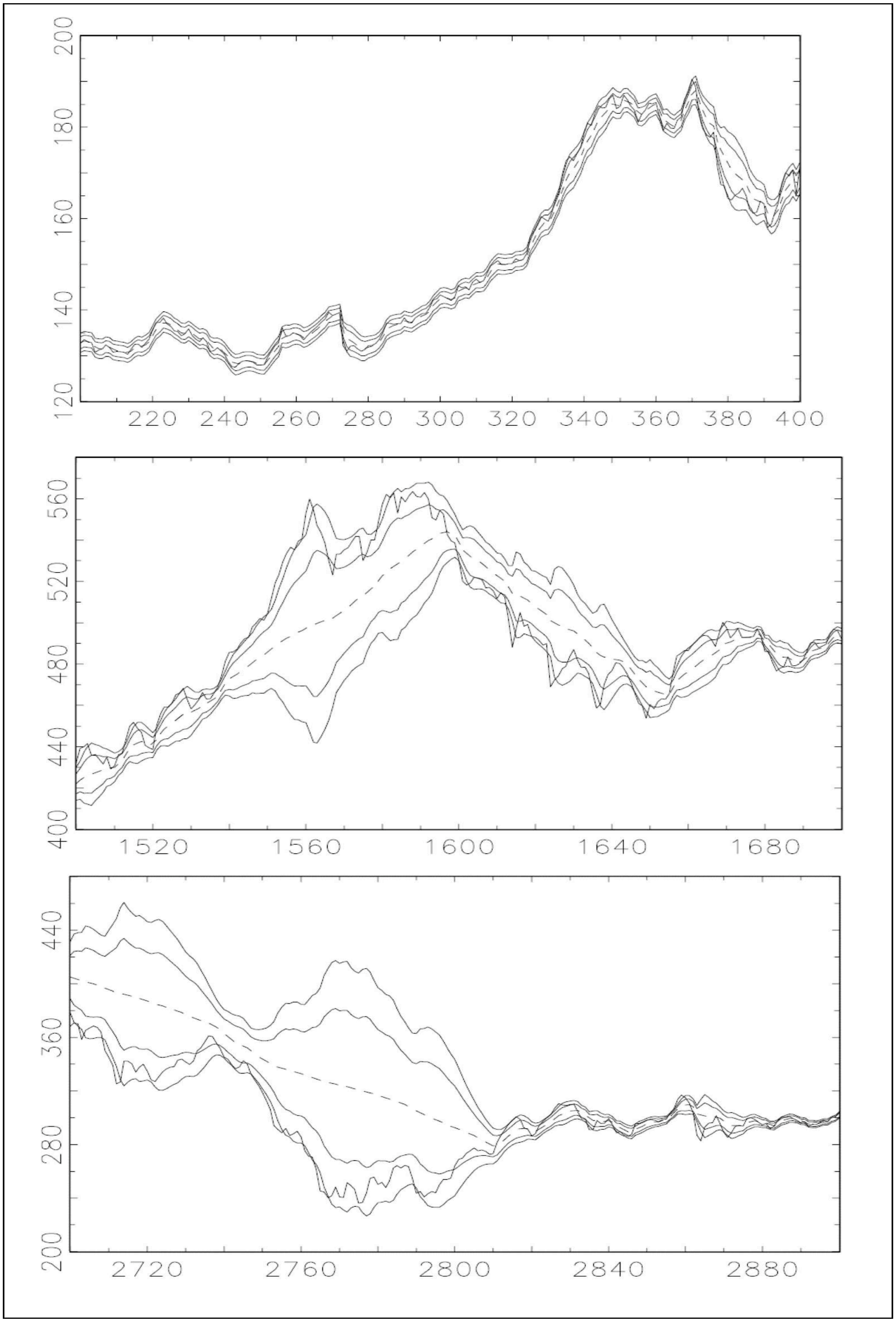


Figure 4.5: Observed prices, estimated fundamental prices and boundaries for figures (a), (b) and (c) from EM data

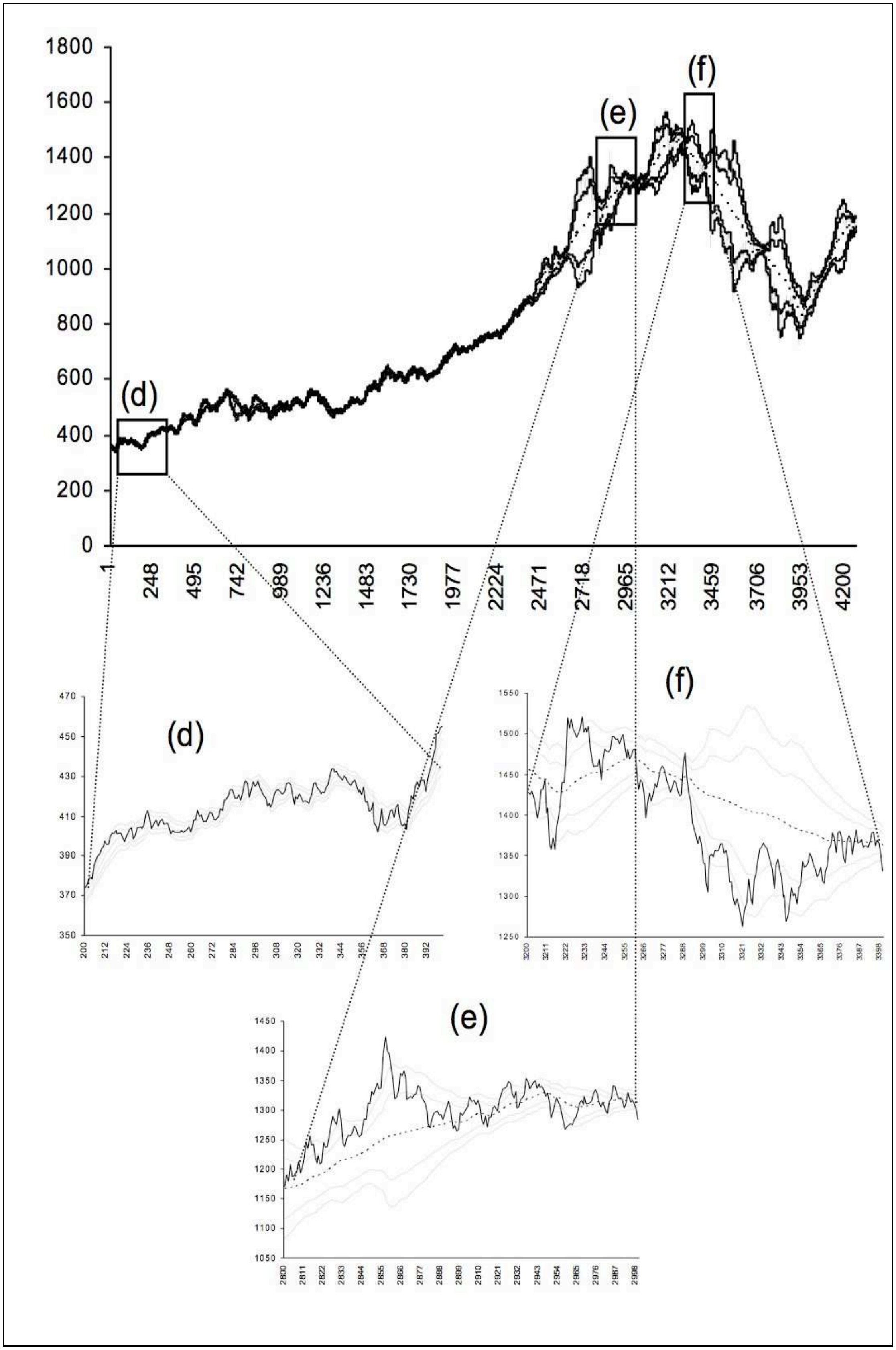


Figure 4.6: Observed prices, estimated fundamental prices and boundaries. EU data.

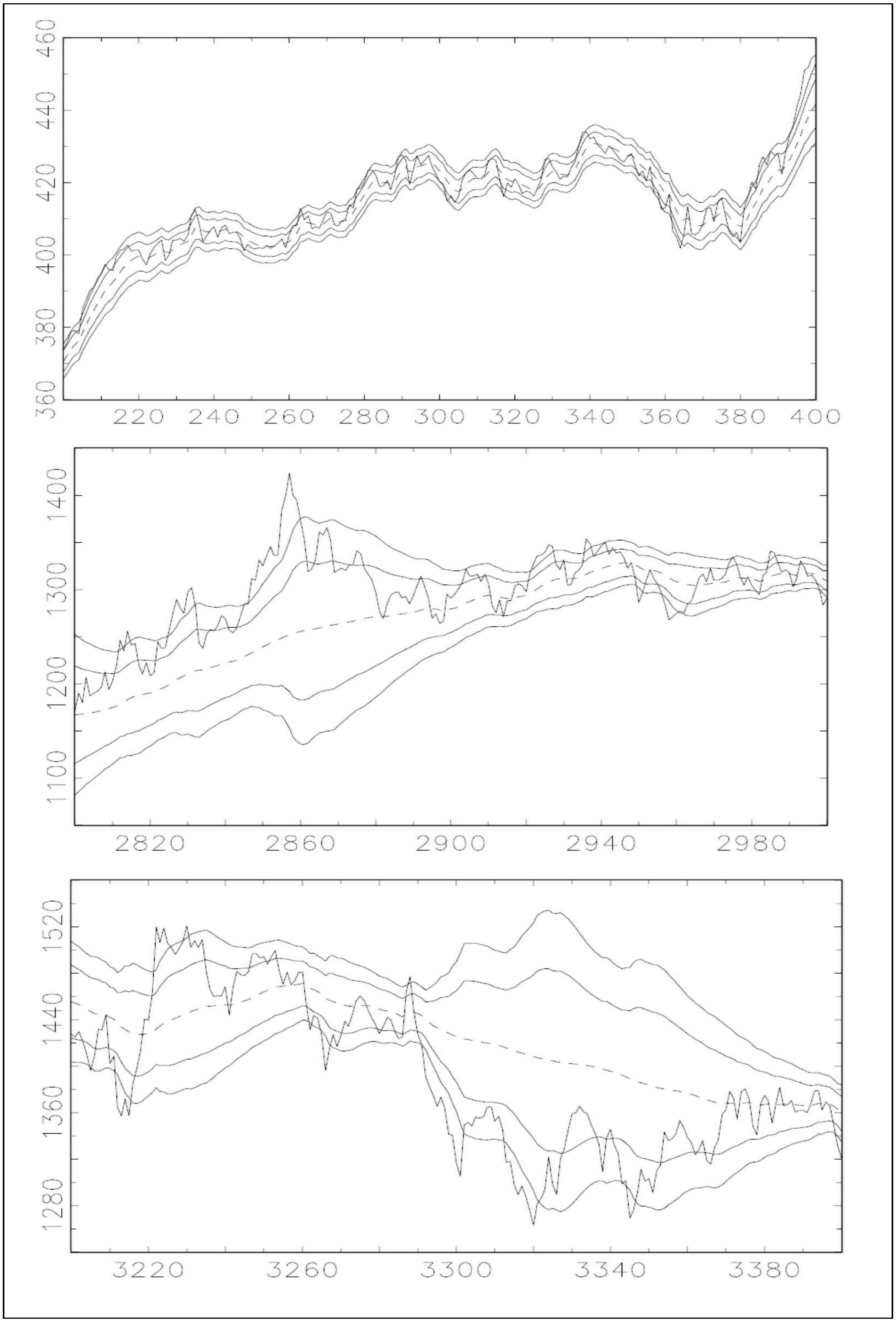


Figure 4.7: Observed prices, estimated fundamental prices and boundaries for figures (d), (e) and (f) from EU data

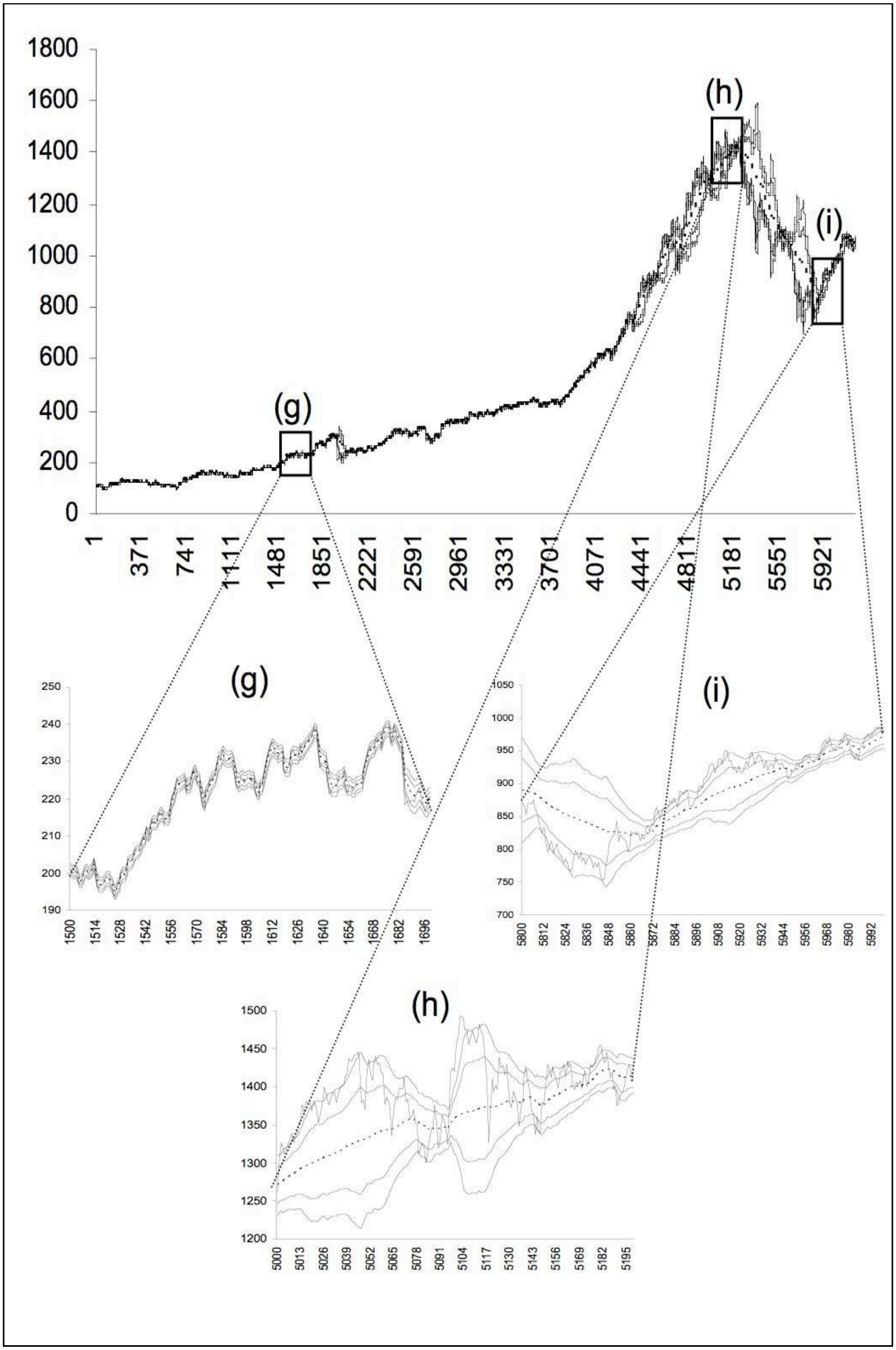


Figure 4.8: Observed prices, estimated fundamental prices and boundaries. US data.

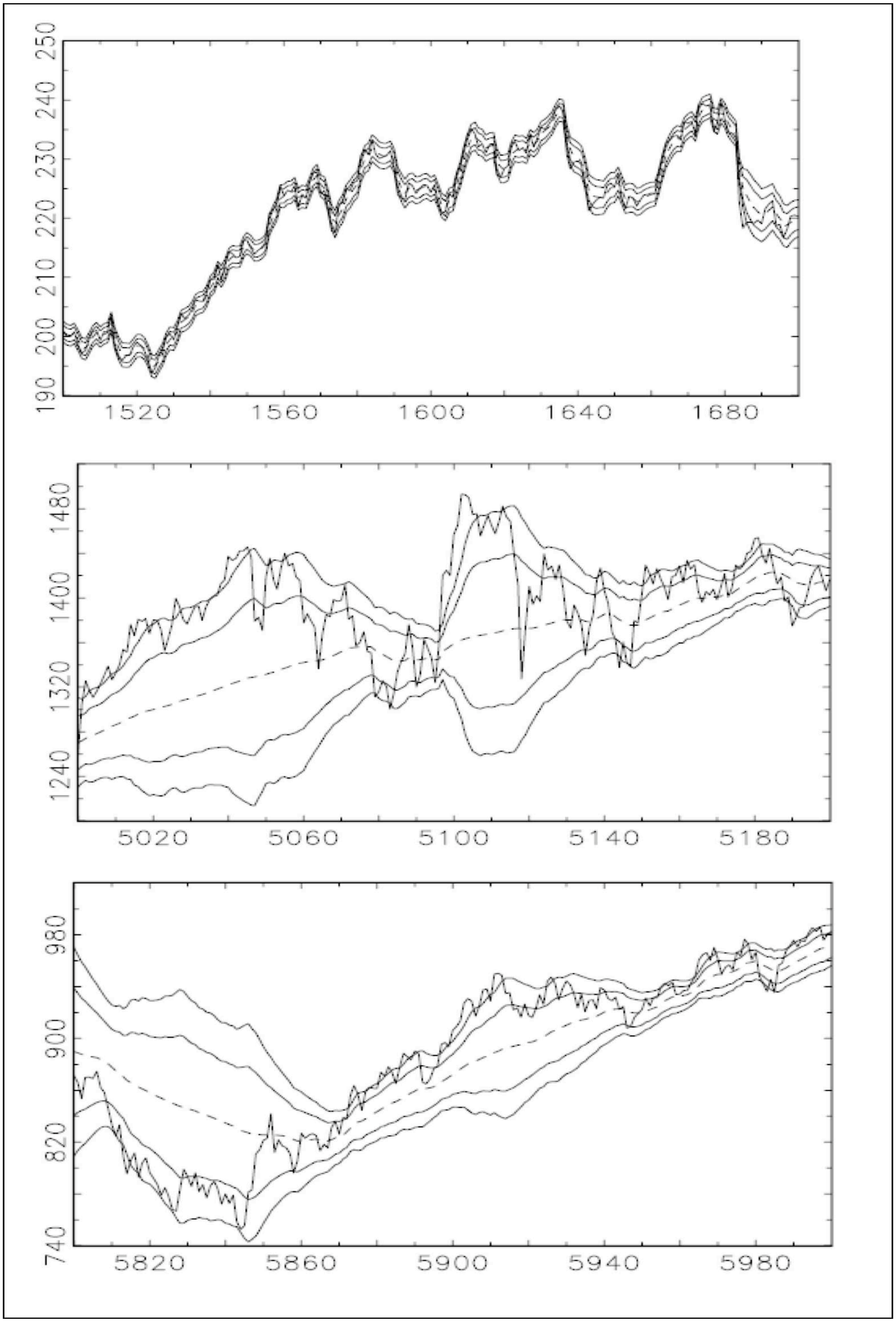


Figure 4.9: Observed prices, estimated fundamental prices and boundaries for figures (g), (h) and (i) from US data

Table 4.1: Estimation results

	EM	EU	USA
ω	0.4041	0.3714	0.0750
	(0.0174)	(0.0308)	(0.0027)
α	0.1510	0.0392	0.0630
	(0.0040)	(0.0014)	(0.0014)
γ	0.0207	0.0089	0.0242
	(0.0023)	(0.0011)	(0.0009)
β	0.6471	0.9164	0.8630
	(0.0085)	(0.0027)	(0.0027)

Entries are estimates of the GJR-GARCH parameters. Numbers in brackets are heteroskedastic-consistent standard errors.

Table 4.2: Percentage in boundaries

	EM	EU	USA
Normal	54.760	49.848	63.849
Unusual	28.234	28.736	23.268
Abnormal	17.006	21.417	12.883

Percentages of observations in normal, unusual and abnormal states.

Table 4.3: Transition Probabilities. 3 states, order 1

	EM			EU			USA		
	N	U	A	N	U	A	N	U	A
N	0.795	0.162	0.043	0.783	0.175	0.042	0.826	0.131	0.043
U	0.337	0.493	0.171	0.305	0.525	0.170	0.390	0.460	0.151
A	0.102	0.320	0.578	0.095	0.230	0.675	0.157	0.327	0.515

Entries are estimates of the transition probabilities for a Markov chain of order one with states Normal, Unusual and Abnormal. Columns are states at $t-1$ and rows at t. For example, the cell $P_{A,N}$ for EM, 0.320, reads as the probability of having illusions of validity at time t given that at $t-1$ observed prices had illusions of control.

Table 4.4: Transition Probabilities. 5 states, order 1

	EM					EU					USA				
	N	U_+	U_-	A_+	A_-	N	U_+	U_-	A_+	A_-	N	U_+	U_-	A_+	A_-
N	0.795	0.091	0.071	0.020	0.023	0.783	0.096	0.080	0.023	0.019	0.826	0.074	0.056	0.025	0.018
U_+	0.391	0.427	0.000	0.183	0.000	0.309	0.504	0.000	0.185	0.001	0.438	0.408	0.001	0.149	0.004
U_-	0.285	0.003	0.552	0.000	0.160	0.301	0.004	0.546	0.000	0.150	0.333	0.008	0.511	0.000	0.148
A_+	0.087	0.315	0.000	0.598	0.000	0.075	0.211	0.000	0.714	0.000	0.106	0.318	0.000	0.576	0.000
A_-	0.118	0.000	0.327	0.000	0.555	0.135	0.000	0.267	0.000	0.598	0.249	0.000	0.344	0.000	0.407

Entries are estimates of the transition probabilities for a Markov chain of order one with states Normal, Unusual+, Unusual-, Abnormal+ and Abnormal-. Columns are states at $t-1$ and rows at t. For example, the cell $P_{A_+,N}$ for EM, 0.118, reads as the probability of no illusions in the observed prices at time t given that at $t-1$ observed prices had optimistic illusions of control.

Table 4.5: Transition Probabilities. 3 states, order 2

	N, N	N, U	N, A	U, N	U, U	U, A	A, N	A, U	A, A
					EM				
N	0.639	0.123	0.032	0.075	0.051	0.036	0.009	0.010	0.024
U	0.260	0.059	0.018	0.115	0.311	0.066	0.020	0.047	0.104
A	0.069	0.029	0.004	0.125	0.138	0.058	0.041	0.209	0.327
					EU				
N	0.624	0.127	0.032	0.074	0.067	0.034	0.010	0.011	0.021
U	0.224	0.068	0.014	0.125	0.327	0.073	0.020	0.058	0.092
A	0.069	0.022	0.004	0.070	0.110	0.050	0.045	0.127	0.503
					USA				
N	0.693	0.100	0.034	0.074	0.039	0.018	0.013	0.017	0.012
U	0.303	0.068	0.018	0.123	0.278	0.059	0.022	0.050	0.078
A	0.113	0.031	0.013	0.115	0.136	0.077	0.050	0.152	0.312

Entries are estimates of the transition probabilities for a Markov chain of order two with states Normal, Unusual and Abnormal. Columns are states at $t-2$ and rows at $t-1$ and t. For example, the cell $P_{A,NU}$ for EM, 0.029, reads as the probability that the observed price at time t has illusions of validity and at $t-1$ it does not have any illusion given that at $t-2$ it had illusions of control.

Table 4.6: Transition Probabilities. 5 states, order 2

EM

	N,N	N,U_+	N,U_-	N,A_+	N,A_-	U_+,N	U_+,U_+	U_+,U_-	U_+,A_+	U_+,A_-	U_-,N	U_-,U_+
N	0.639	0.069	0.054	0.014	0.018	0.041	0.031	0.000	0.020	0.000	0.035	0.000
U_+	0.297	0.055	0.022	0.012	0.005	0.138	0.225	0.000	0.063	0.000	0.000	0.000
U_-	0.225	0.011	0.031	0.010	0.010	0.003	0.000	0.000	0.000	0.000	0.090	0.000
A_+	0.052	0.026	0.005	0.000	0.003	0.134	0.121	0.000	0.060	0.000	0.000	0.000
A_-	0.087	0.009	0.017	0.000	0.006	0.000	0.000	0.000	0.000	0.000	0.116	0.003

	U_-,U_-	U_-,A_+	U_-,A_-	A_+,N	A_+,U_+	A_+,U_-	A_+,A_+	A_+,A_-	A_-,N	A_-,U_+	A_-,U_-	A_-,A_+	A_-,A_-
N	0.020	0.000	0.016	0.003	0.004	0.000	0.013	0.000	0.006	0.000	0.006	0.000	0.012
U_+	0.000	0.000	0.000	0.020	0.063	0.000	0.099	0.000	0.000	0.000	0.000	0.000	0.000
U_-	0.393	0.000	0.068	0.000	0.000	0.000	0.000	0.000	0.019	0.000	0.032	0.000	0.108
A_+	0.000	0.000	0.000	0.039	0.192	0.000	0.367	0.000	0.000	0.000	0.000	0.000	0.000
A_-	0.153	0.000	0.055	0.000	0.000	0.000	0.000	0.000	0.043	0.000	0.228	0.000	0.283

EU

	N,N	N,U_+	N,U_-	N,A_+	N,A_-	U_+,N	U_+,U_+	U_+,U_-	U_+,A_+	U_+,A_-	U_-,N	U_-,U_+
N	0.624	0.071	0.056	0.018	0.014	0.039	0.037	0.000	0.020	0.000	0.035	0.000
U_+	0.227	0.058	0.010	0.013	0.000	0.128	0.301	0.000	0.073	0.001	0.000	0.000
U_-	0.220	0.007	0.059	0.000	0.014	0.000	0.002	0.000	0.002	0.000	0.121	0.002
A_+	0.056	0.012	0.005	0.002	0.000	0.063	0.095	0.000	0.053	0.000	0.000	0.000
A_-	0.093	0.006	0.026	0.000	0.010	0.000	0.000	0.000	0.000	0.000	0.084	0.000

	U_-,U_-	U_-,A_+	U_-,A_-	A_+,N	A_+,U_+	A_+,U_-	A_+,A_+	A_+,A_-	A_-,N	A_-,U_+	A_-,U_-	A_-,A_+	A_-,A_-
N	0.030	0.000	0.015	0.004	0.007	0.000	0.012	0.000	0.006	0.000	0.004	0.000	0.009
U_+	0.000	0.000	0.000	0.022	0.055	0.000	0.107	0.000	0.000	0.000	0.000	0.000	0.001
U_-	0.355	0.000	0.068	0.000	0.000	0.000	0.000	0.000	0.016	0.000	0.061	0.000	0.072
A_+	0.000	0.000	0.000	0.035	0.126	0.000	0.553	0.000	0.000	0.000	0.000	0.000	0.000
A_-	0.138	0.000	0.045	0.000	0.000	0.000	0.000	0.000	0.064	0.000	0.129	0.000	0.405

USA

	N,N	N,U_+	N,U_-	N,A_+	N,A_-	U_+,N	U_+,U_+	U_+,U_-	U_+,A_+	U_+,A_-	U_-,N	U_-,U_+
N	0.693	0.056	0.044	0.020	0.014	0.045	0.020	0.000	0.008	0.001	0.029	0.001
U_+	0.346	0.059	0.012	0.015	0.005	0.124	0.218	0.000	0.067	0.000	0.001	0.000
U_-	0.253	0.021	0.044	0.006	0.009	0.003	0.005	0.000	0.000	0.000	0.117	0.002
A_+	0.084	0.014	0.000	0.008	0.000	0.126	0.128	0.000	0.065	0.000	0.000	0.000
A_-	0.165	0.021	0.042	0.007	0.014	0.000	0.000	0.000	0.000	0.000	0.095	0.000

	U_-,U_-	U_-,A_+	U_-,A_-	A_+,N	A_+,U_+	A_+,U_-	A_+,A_+	A_+,A_-	A_-,N	A_-,U_+	A_-,U_-	A_-,A_+	A_-,A_-
N	0.017	0.000	0.009	0.007	0.011	0.000	0.007	0.000	0.006	0.000	0.006	0.000	0.006
U_+	0.000	0.000	0.000	0.012	0.046	0.000	0.091	0.000	0.000	0.000	0.001	0.000	0.003
U_-	0.344	0.000	0.049	0.000	0.000	0.000	0.000	0.000	0.035	0.000	0.053	0.000	0.059
A_+	0.000	0.000	0.000	0.033	0.159	0.000	0.383	0.000	0.000	0.000	0.000	0.000	0.000
A_-	0.151	0.000	0.098	0.000	0.000	0.000	0.000	0.000	0.081	0.000	0.140	0.000	0.186

Entries are estimates of the transition probabilities for a Markov chain of order two with states Normal, Unusual+, Unusual-, Abnormal+ and Abnormal-. Columns are states at $t-2$ and rows at $t-1$ and t. For example, the cell P_{A_+,NU_+} for EM, 0.026, reads as the probability that the observed price at time t has optimistic illusions of validity and at $t-1$ it does not have any illusion given that at $t-2$ it had optimistic illusions of control.

Table 4.7: Transition Probabilities. 3 states, order 3

EM

	N,N,N	N,N,U	N,N,A	N,U,N	N,U,U	N,U,A	N,A,N	N,A,U	N,A,A	U,N,N	U,N,U	U,N,A	U,U,N
N	0.521	0.093	0.025	0.056	0.039	0.028	0.008	0.007	0.018	0.060	0.012	0.003	0.023
U	0.201	0.047	0.012	0.028	0.017	0.013	0.002	0.006	0.011	0.085	0.021	0.009	0.060
A	0.048	0.017	0.004	0.017	0.008	0.004	0.000	0.000	0.004	0.096	0.025	0.004	0.019

	U,U,U	U,U,A	U,A,N	U,A,U	U,A,A	A,N,N	A,N,U	A,N,A	A,U,N	A,U,U	A,U,A	A,A,N	A,A,U	A,A,A
N	0.018	0.010	0.007	0.010	0.019	0.005	0.003	0.000	0.005	0.003	0.002	0.004	0.007	0.013
U	0.222	0.030	0.005	0.017	0.044	0.015	0.004	0.001	0.024	0.019	0.004	0.011	0.040	0.053
A	0.090	0.028	0.003	0.018	0.037	0.029	0.011	0.001	0.069	0.095	0.045	0.011	0.120	0.197

EU

	N,N,N	N,N,U	N,N,A	N,U,N	N,U,U	N,U,A	N,A,N	N,A,U	N,A,A	U,N,N	U,N,U	U,N,A	U,U,N
N	0.506	0.096	0.022	0.053	0.046	0.027	0.007	0.008	0.018	0.055	0.015	0.004	0.024
U	0.170	0.040	0.014	0.029	0.031	0.008	0.005	0.004	0.005	0.091	0.031	0.003	0.060
A	0.047	0.018	0.004	0.010	0.007	0.005	0.002	0.002	0.000	0.051	0.014	0.004	0.032

	U,U,U	U,U,A	U,A,N	U,A,U	U,A,A	A,N,N	A,N,U	A,N,A	A,U,N	A,U,U	A,U,A	A,A,N	A,A,U	A,A,A
N	0.032	0.011	0.005	0.013	0.016	0.007	0.003	0.000	0.003	0.005	0.002	0.004	0.006	0.011
U	0.224	0.043	0.007	0.026	0.040	0.014	0.006	0.000	0.020	0.024	0.013	0.011	0.022	0.060
A	0.064	0.014	0.005	0.013	0.032	0.034	0.008	0.003	0.035	0.065	0.027	0.022	0.084	0.396

USA

	N,N,N	N,N,U	N,N,A	N,U,N	N,U,U	N,U,A	N,A,N	N,A,U	N,A,A	U,N,N	U,N,U	U,N,A	U,U,N
N	0.587	0.080	0.025	0.058	0.027	0.014	0.011	0.013	0.010	0.061	0.010	0.003	0.017
U	0.241	0.040	0.022	0.036	0.026	0.006	0.004	0.008	0.006	0.091	0.026	0.005	0.053
A	0.086	0.023	0.005	0.013	0.010	0.009	0.006	0.004	0.003	0.081	0.025	0.009	0.043

	U,U,U	U,U,A	U,A,N	U,A,U	U,A,A	A,N,N	A,N,U	A,N,A	A,U,N	A,U,U	A,U,A	A,A,N	A,A,U	A,A,A
N	0.017	0.005	0.006	0.006	0.007	0.011	0.002	0.001	0.010	0.004	0.003	0.003	0.004	0.005
U	0.195	0.031	0.005	0.022	0.032	0.013	0.006	0.003	0.017	0.021	0.012	0.008	0.027	0.043
A	0.068	0.025	0.004	0.023	0.050	0.037	0.011	0.003	0.034	0.077	0.042	0.020	0.083	0.209

Entries are estimates of the transition probabilities for a Markov chain of order thee with states Normal, Unusual and Abnormal. Columns are states at $t-3$ and rows at $t-2$, $t-1$ and t. For example, the cell $P_{A,NUA}$ for EM, 0.004, reads as the probability that the observed price at time t has illusions of control, at $t-1$ it has illusions of validity and at $t-2$ it does not have any illusion given that at $t-3$ it had illusions of control.

4.5 Conclusions

In this chapter, we studied the possibility of markets been endowed with emotional components which affect the significance of the informational content of prices. Using a state space model we study the presence of the illusions of validity, the illusion of control and clustering illusion in financial markets and their impact on the informational content of prices.

In order to provide a neurofinancial examination of noise embedded in financial markets, we rely on our own personal interpretation of a very well known state space model, called local level model conjecturing about the correspondence between the partitions of the returns and different types of emotions. While doing this, we aim to integrate psychology and economics providing a way of quantifying psychological phenomena extensively studied by cognitive psychologists.

The view that prices may be driven by emotions opens the door to a new paradigmatic conception that we call *illusionary finance* which is based in evolutionary finance, cognitive psychology, behavioral finance and tries to provide some explanations about why there is a tremendous need in financial markets to avoid dealing with random events.

In the search of plausible explanations to random events, market participants believe things that are not true and bias their evaluation of new information in such way that they see what they expect to see, and conclude what they want to conclude. In order to validate information that is consistent with pre-existing beliefs, market participants may use technical analysis as a way to detect paths and predict future behavior of prices. This chapter shows that illusions are present in financial markets, and impact on the informational content of prices. Prices are supposed to yield knowledge but when prices are polluted with illusion the link between prices and knowledge vanishes.

One big problem is that there might be many market players who are not aware that prices might not be yielding knowledge all the time. Moreover, there might be many traders taking advantage of this situation coming out of the blue with a bunch of trading strategies to profit with the unawareness of the others.

Given that illusions are not eliminated by repeated examinations, and the reluctancy of people to accept that they were wrong, traders profiting from the unawareness of the others may persist in time. If that is true, them we should be dealing with illusionary markets where markets prices are driven by the emotes and the information embedded in prices should be deeply scrutinized.

4.6 Appendix A

This technical appendix aims to provide some details about how the model is adjusted in order to apply the Kalman Filter.

The methodology employed relies on Harvey, Ruiz and Sentana (1992), Harvey et al (2004), and Kim and Nelson (1999)

P_t and F_t are the so called measurement and transition equation of the state space model written in the beginning of Section 4.2. The GJR-GARCH model in (4.1) is defined on the innovation, called the emotional component, of the observed prices in the measurement equation. The model can be rewritten as:

$$\begin{pmatrix} F_t \\ E_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} F_{t-1} \\ E_{t-1} \end{pmatrix} + \begin{pmatrix} u_{F,t} \\ \varepsilon_{E,t} \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix} \begin{pmatrix} u^*_{F,t} \\ \varepsilon^*_{E,t} \end{pmatrix} \tag{4.4}$$

where

$$\begin{pmatrix} u_{F,t} \\ \varepsilon_{E,t} \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix} \begin{pmatrix} u^*_{F,t} \\ \varepsilon^*_{E,t} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Omega_t\right) \tag{4.5}$$

and

$$\Omega_t = \begin{pmatrix} \sigma^2_{F,t} & 0 \\ 0 & 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & \sigma^{*2}_{E,t} \end{pmatrix} \tag{4.6}$$

where $\sigma^{*2}_{E,t}$ follows a GJR-GARCH.

This model cannot be estimated by the standard Kalman filter since we will need to know $\widehat{\sigma}^2_F$, which would appear in the prediction equation of the filter. The problem is that the GJR-GARCH depends on past unobserved shocks, and even the knowledge of past factors does not imply the knowledge of past unobserved shocks. However, the problem can be solved by replacing past shocks by their conditional expectations

$$\sigma^{*2}_{E,t} = \omega + \alpha E(\xi^{*2}_{E,t-1}) + \gamma E(\xi^{*2}_{E,t-1} d_{t-1}) + \beta \sigma^{*2}_{E,t-1} \tag{4.7}$$

where $\xi^*_{E,t-1} = \varepsilon^*_{E,t}/\sigma^*_{E,t}$ is the standardized shock.

Therefore the above equation represents an approximation of the real process (4.1), hence the quasi-optimal term proposed by Harvey et al. (1992) can be applied. To obtain the conditional expectations, the state is augmented yielding new measurement and transition equations as follows:

$$P_t = \begin{pmatrix} 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} F_t \\ E_t \\ \varepsilon^*_{E,t} \end{pmatrix} \tag{4.8}$$

and

$$\begin{pmatrix} F_t \\ E_t \\ \varepsilon^*_{E,t} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} F_{t-1} \\ E_{t-1} \\ \varepsilon^*_{E,t-1} \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} u_{F,t} \\ \varepsilon_{E,t} \\ \varepsilon^*_{E,t} \end{pmatrix} \tag{4.9}$$

where

$$\begin{pmatrix} \varepsilon_{F,t} \\ \varepsilon_{E,t} \\ \varepsilon^*_{E,t} \end{pmatrix} \sim N \left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \Omega_t \right) \tag{4.10}$$

$$\Omega_t \begin{pmatrix} \sigma^2_{F,t} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \sigma^{*2}_{E,t} \end{pmatrix} \tag{4.11}$$

The restriction $\sigma^2_{E,t} = 0$ in the diagonal of Ω_t is necessary to identify $\sigma^{*2}_{E,t}$ and ω. Thus, using equations (4.4) to (4.8) the model can be estimated by the standard Kalman filter

CHAPTER 5

Illusions and the Construction of Illusionary Finance

Cognitive illusions are psychological complexities which have been extended beyond the judgement and decision making field. Illusions represent the conscious or unconscious possibility of having a biased belief driven by fast thinking and the use of heuristics; or the possibility of someone taking advantage of human failure in objective thinking in order to maximize his own profit

This chapter aims to summarize the main psychological, and neurophysiological tools that have been recently incorporated in the study of financial markets and financial decision making on which our proposed new approach of understanding financial markets (i.e. illusionary finance) is based.

5.1 Illusions

As we have pointed out in chapter 1 The term **illusion** comes from the Latin verb *illudere* which means "to mock at, to make fun of, to ridicule"[1]. An illusion denotes the action of deceiving, the state or fact of being intellectually deceived or misled or something that deceives or misleads intellectually, the perception of something objectively existing in such a way as to cause misinterpretation of its actual nature, or a misleading image presented to the vision.[2]

In this chapter we focus on cognitive illusions, emphasizing their occurrence in financial markets and how illusionists can take advantage of them in order to fool other market partici-

[1]Latin-English dictionary, http://humanum.arts.cuhk.edu.hk/Lexis/Latin/.
[2]Merriam-Webster Online dictionary, http://www.m-w.com/dictionary.

pants. Our aim is to present an extensive list of cognitive illusions which will be the foundation of the illusionary finance paradigm presented in the following chapter.

5.2 Cognitive illusions

Cognitive illusions represent a special category of illusions associated with cognitive processes, i.e. processes such as memory, attention, perception, action, problem solving and mental imagery[3].

The existence of cognitive illusions is a fact. However, there are still numerous open questions regarding the processes responsible for their emergence and evolvement. In this context, psychological research (Gheorghiu, Molz, and Pohl (2004a)) points out that cognitive illusions represent a mixture of immediate (automatic) and mediate (deliberate) reaction patterns. While an automatic reaction takes place reflex-like, a deliberate reaction implies a conscious choice of the strategy of reaction. This strategy can be based on rational judgments (rational strategy), rely on the evaluation of alternatives on the basis of suggestive cues (suggestive strategy), use suggestive cues and involve emotions (intuitive strategy), or simply be random (random strategy). In common practical situations, suggestive and intuitive strategies proved to be favored due to their simplicity, rapidity of use, and good performance at least with respect to certain categories of tasks. This qualifies them for convenient strategies in a fast-changing and uncertain environment, such as the financial markets.

In spite of their original labelling as departures from rationality and failures of the cognitive system (Tversky and Kahneman (1974)), cognitive illusions are to date understood in a broader (evolutionary) context. Accordingly, cognitive illusions naturally develop during the evolution of human species as a result of repeated trials and errors, and serve as adaptive tools in an constantly and fast changing, uncertain and complex environment. Gigerenzer et al. (1999) mention several substantial adaptive advantages ensured by the employment of illusions in everyday life, such as orientation at a suggestive direction, support for survival through the activation of potential capacities and reduction of undesired consequences, or protection against inner dissonances or social isolation.

According to Pohl (2004a), the cognitive illusions can be ranked in three main categories:

A. illusions of thinking - which consist in the false application of a certain information processing rule,

B. illusions of judgement - that develop when specific attributes of a situation (such as subjective experience, selective memory activation, feelings of familiarity or confidence, etc.) affect judgments,

C. illusions of memory - which refer to memories that systematically deviate from the original earlier encoded material.

We note that this categorization is rather a formal one. In principle, none of the cognitive illusions known can be fully segregated from the others. Complex links based on mutual influence, causality, or overlapping can be detected between and within the three classes of illusions

[3] http://www.answers.com/topic/cognition.

defined above. For example illusions of change and stability can derive from anchoring or hindsight bias, representativeness can yield to base-rate neglect, anchoring to labelling, illusions of control can rely on overconfidence, confirmation biases arise because of availability of certain information, etc.

Due to the fact that individual beliefs form the basis of individually stored information, the distorted encoding and processing of this information leads to biased convictions, thus biased actions. Given that in financial markets, subjective investor beliefs directly impact on investment decisions, hence in market prices, cognitive illusions can have a considerable impact on price evolution and market events in general.

From an economic perspective, we further define the **illusions in financial markets** as a subcategory of cognitive illusions with direct reference to financial markets. They represent delusive information intentionally created and spread by certain traders (referred as *illusionary traders*) in order to mislead other market participants and to take advantage of their biased reactions. This false information is shaped for the purpose of inducing cognitive illusions of the types illustrated below. This type of mechanism operates as an illusion if the addressees actually perceive it as valuable information and act on it.

In other words, illusionary traders are aware of the predisposition of other individuals who take part in the trade towards cognitive illusions, and dispose of adequate knowledge concerning the mechanisms and consequences of these illusions. Thus, they try to manipulate cognitions of other traders in their favor. Following the definition of Gheorghiu, Molz, and Pohl (2004a), we can stress that, using different illusive techniques, illusionary traders aim to exploit the illusionability of other investors in order to create an illusive situation.

As noted by Shefrin (2000), in order to interpret the investor behavior that dictates the course of financial markets, it is important to understand the illusions as documented in psychological studies. Following the categorization proposed by Pohl (2004a), we subsequently present the main results of psychological research with respect to different types of cognitive illusions. The definition of each illusion is followed by a brief exposition of the theoretical attempts and/or empirical results meant to explain the way it arises. On occasion, we also try and point out examples of financial phenomena that rely on the referred illusion and suggest how this can be exploited by an illusionary trader. We stress that, given the relatedness of different cognitive illusions, they become manifest simultaneously. Thus, the most part of anomalies observed in financial markets have manifold roots and can be ascribed to multiple illusions. Similarly, illusionary traders can resolve to induce several illusions at the same time for the purpose of generating manageable effects for their own benefit.

5.2.1 Illusions of thinking

Several cognitive illusions consist in the incorrect use of what are considered to be axiomatic rules of thinking and can be hence included in the category of illusions of thinking:

- ◇ *Conjunction fallacy* - arises when individuals assign a higher probability to the compound of two events than to the single events alone.

Several theories were developed to the purpose of explaining this fallacy. Some of these theories focuss on different phenomena identified to be triggers of the conjunction fallacy, such as the heuristic of representativeness originally referred in the work of Kahneman and Tversky or the fast and frugal heuristics introduced by Gigerenzer. Others are more extensive, such as the surprise theory of Shackle (1969) (which considers the degree of surprise produced by the occurrence of an event as a subjective measure of uncertainty) or the cognitive self theory of Donovan and Epstein (1997) (which refers to the interaction of two different cognitive systems involved in reasoning and decision making: a rational and an experiential one, where the latter is the default one and operates using heuristic strategies). However, no comprehensive and satisfactory explanation of this fallacy has been yet found. (cf. Fisk (2004).)

Illusionary traders can generate an illusion of this type if they temporary shape their trades in order to reinforce an already established price trend (e.g. they buy stocks with already up-going prices). Observing their actions, other investors become (more) confident in a continuation of the price evolution in the same direction and more eager to imitate illusionary traders. The reason is that they perceive the probability of the two events: (a) positively (negatively) sloping prices and (b) the existence of market participants interested in buying (selling) the stock, as being higher than the one of only one of those events. This entails an excessive price increase the illusionary traders can benefit from.

◇ *Base-rate fallacy* - represents the tendency of people to disregard prior information in formulating their judgments.

Kahneman and Tversky were the first to account for the base-rate fallacy as the principal source of bias with respect to what was considered to be the "correct" way of forming opinions (i.e. the Bayesian inference). This came to contradict the results of previous research (Edwards (1968), Wallsten (1972)) which had found that subjects rather judge in a conservative manner, i.e. they overweight base-rate information against new evidence. More recent results based on the scale-adjustment averaging model of Birnbaum and Stegner (1979) attempt to give a more complete answer to the problem of beliefs formation. They account for the directional impact of different information pieces which inversely depends on the number and total weight of other sources of information and varies in time.

The base-rate fallacy draws upon different factors with impact on those judgments that should theoretically rely on Bayesian inference, such as: the format of available statistical information (e.g. the use of natural frequencies can facilitate the correct application of the Bayes formula, because, according to Gigerenzer and Hoffrage (1995), people deal easier with natural frequencies than with probability formats), experimental design-features (such as within-subjects variation, according to Birnbaum and Mellers (1983)), the causality of base-rate information (Tversky and Kahneman (1980)), and source credibility (Birnbaum and Mellers (1983)). (cf. Birnbaum (2004), Kurzenhaeuser and Luecking (2004).)

As a possible application with direct reference to financial decisions, we underline the effect of certain news (especially the ones accompanied by surprise and/or acute consequences, such as wars, market crashes, etc., because of their increased availability) that get around to change previous opinions concerning the market evolution. In revising their beliefs, investors simply discard past information and exclusively rely on new evidence.

With respect to the illusionary trading, some market participants can be interested in spreading news with appropriate formats that render the respective information sufficiently penetrating, in order to overweight other investors and thus to prevail in their opinions.

◇ *Confirmation bias* - denotes the selective search for new information, the interpretation or remembering of existing evidence in a confirmative way.

Its occurrence can be characterized as being more or less unintentional, because the search for results that confirm one's own hypothesis, if such results can be found (positive test strategy), appears difficult to avoid. The motivation is that such strategies functions as heuristics (strategies which already proved to be effective), and there is hence no need to change them. However, a positive test strategy is shown to be biased only for tests with deficient diagnostic and can be avoided when subjects apply the same strategy for both their hypothesis and alternative explanations.

While people do not necessarily search for confirmation in testing their assumptions, the verification of already established or of motivationally supported hypothesis (where the latter imply emotions) can be affected by the confirmation bias. In the case of an emotional hypothesis, the intensity of its effect depends on the costs of the erroneous decision. If the erroneous acceptance is costly, people try and truly test their hypotheses, while high costs of an erroneous rejection results in a more probable confirmation of the undesired hypothesis. (cf. Oswald and Grosjean (2004).)

An anecdotic example mentioned by Barberis and Thaler (2003), p. 1066, refers to the belief perseverance of academics in the Efficient Market Hypothesis which can be understood as a manifestation of the confirmation bias. We could extend it to the reluctance to behavioral arguments.
Furthermore, the confirmation bias provides an explanation for the well-documented underreaction of investors to the release of firm-specific information (Jegadeesh and Titman (1993)), due to the fact that people tend to look for confirmatory information and to discard new evidence that does not accommodate with their beliefs.

Sending false information meant to sustain beliefs in the continuation of a certain price evolution (such as buying signals for stocks that performed well in the past and are hence judged as good investments), when private information indicates reversals in this evolution, can procure great advantages to illusionary traders (and represents a way private information is actually exploited in the market).

◇ *Illusory correlation* - refers to the dependence mistakenly found between unrelated events or different information items.

The sources of illusory correlation apply to: an overweighed impact of prior expectations (when correlations are seen there where they are expected to be found), an unequal weighting of different attribute levels (e.g. the presence of both cause and effect is overweighted relative to the absence of both), selective attention and encoding (e.g. in the case of rare events), or sample-sizes (where small samples are perceived as representative as larger ones)[4].

However, given that the ability to recognize and estimate correlations between object attributes represents an important characteristic of adaptive intelligence, illusory correlation should not be considered as a sign of irrationality. (cf. Fiedler (2004).)

In financial markets, investors frequently fall prey to an illusory correlation between the success of a company and the performance of its stocks. Thus, they believe that stocks of good companies have to represent valuable investments, while stocks of bad companies shall be bad too. Looking at historical data, exactly the contrary of this conviction proves to be true (Shefrin and Statman (1995)).

Also, traders are inclined to follow the advice (and even more ardently the actions) of different gurus of financial markets, suspecting the existence of a positive correlation between the information these persons are supposed to dispose of and the future prospects of the assets their statements pertain to. Anecdotal evidence shows that such traders tergiversate the reality most of the time. Yet the distributors of such information can highly profit of the induced illusory correlations.

◇ *Illusion of control* - consists in the overestimation of the personal influence over outcomes.

Early research of Langer (1975) has motivated the control illusion by means of the confusion between skill and chance. Thompson, Armstrong, and Thomas (1998) offer another explanation based on the so-called control heuristic which represents a shortcut in assessing control. This heuristic comprises both the intention to reach the outcome and the perceived link between action and the desired outcome. The fact that both elements can manifest themselves even in the absence of control entails an overestimation of control capacity.

Experimental evidence emphasizes the existence of five influence factors with respect to control judgments: skill-related factors (attributes mistakenly associated with the involvement of skills), success or failure emphasis (e.g. the expectation of success which fosters the control illusion, or the expectation of failure which, in contrast, undermines it), the need or desire for the outcome (if there is a motivation to believe in the existence of personal control, such as a monetary incentive for achieving the outcome), mood (e.g. a positive mood increases the probability of the control illusion), and the intrusion of reality (which can reduce or even eliminate the illusionary state).

The consequences of the control illusion can be negative (such as disappointment, pursuit of unrealistic aims, defective protection capacity against harm, etc.), but can also lead to better motivation, increased self-esteem, etc. In effect, depending on the environmental situation, the control illusion can manifest itself in an adaptive way (i.e. exhibit positive consequences) or be rather maladaptive. (cf. Thompson (2004).)

Shareholders like to believe that they can exert a certain control over their shares. This can explain the preference for dividends which are perceived as income, money that can be immediately spent, and not as capital.

[4]The false representativeness of small samples induces further biases in deductive reasoning (see below), because people tend to generalize the conclusions drawn for small samples over the entire population under discussion.

◇ *Biases in deductive reasoning* - can arise during the verification of conclusions following from given information.

If we consider logic to be a satisfactory measure of rationality, then systematic departures from logical solutions will represent biases. These biases arise because people neglect logically relevant information or are influenced by factors unrelated to the logic of the problem. The most well-known of them are: the *confirmation bias* (discussed above) and the *matching bias* (the tendency to focus on the explicit content of sentences, even when they contain negations that fully change their meaning). It has been proven that the content and context of framing of the deductive problem exert a high influence on judgments, hence can reduce or eliminate these fallacies.

However, we should be careful in interpreting these results. First because the statement that logic provides a sufficient framework for assessing rationality is not necessarily true. Second, artificial experimental environments (such as the ones generated in the laboratory and used for the majority of studies) may be unrepresentative for real situations. Third, personal interpretations of the task can yield different results.

However, taking the existence of biases in deductive reasoning as given, researchers looked for sustainable explanations of their emergence. One is provided by the dual system theory which states that two different cognitive systems are activated in the course of thinking: one implicit (helpful in order to fastly contextualize new problems on the basis of prior knowledge) and the other one abstract (needed for the purpose of solving abstract tasks where prior information is irrelevant). The former system appears to diminish the ability to solve abstract tasks (as mostly presented in laboratory experiments) and to generate the type of illusion under discussion. (cf. Evans (2004).)

A financial example for biased deduction pertains to the fact that managerial performance is often mistaken for above-average skills, while the role of chance is totally overlooked (Shefrin (2000)). Thus, managers who know how to maintain the impression of exceptional skills (e.g. by imitating the decisions of their benchmarks or playing other games meant to narrow the transparency of the investors' decisional frames) keep hold of the shareholders' votes and support for a long time.
Moreover, companies may be interested in inducing biased deductive reasoning on the part of financial analysts knowing that the earnings forecasts they issue directly make an impact on the investor trading behavior. For example according to Shefrin (2000), knowing that prices raise when forecasts are lower than actual earnings, companies try and make analysts to pessimistically appreciate their prospects (by preannouncing, manipulating earnings, etc.).

Illusionary traders can exploit the matching bias by sending signals (re)shaped in such a way that they falsely appear to be in accord with general beliefs, hence reinforcing these beliefs and the actions they result in.

5.2.2 Illusions of judgment

A second category of cognitive illusions relates to judgmental deviations from reality and can be summarized by the three *basic heuristics* introduced *by Kahneman and Tversky (1974)*:

◇ *Availability* - pertains to the ease of retrieval or to the amount of recalled information that is relevant for a class of objects.

Two factors have shown their influence on availability: biased encoding and retrieval of information (e.g. caused by the increased frequency of its presentation), and its vividness (reflected in the intensity of the impression produced on the senses). Both factors appear to exhibit higher magnitudes when people are unable to adopt the perspectives of others.

Per definition, availability can refer either to the ease (accessibility) or to the amount of recall. The question which of these two elements are people inclined to base their judgments on, when they retrieve information from memory depends on several factors, such as: individual motivation (e.g. low motivated subjects tend to appeal to the ease of recall, while highly motivated ones rather account for the amount of recall), the direct access to relevant information (which alleviates the need to rely on accessibility), or the perceived diagnosticity of the experienced ease (i.e. people use their recall experience only if they consider it powerful enough in order to distinguish between states, hence to form judgments). Furthermore, people appear to project their naive beliefs about the experience of ease (or difficulty of recall) on their further experiences. (cf. Reber (2004).)

Coming back to financial markets, it is well known how hot news (that are intensively presented and commented in the medias) or vivid memories of singular events of high impact on the price course (such as market crashes, political events, wars, etc.) engrain in investors' minds and exert considerable influence on their decisions.
Empirical studies (French and Poterba (1991)) emphasize the tendency of investors to built insufficiently diversified portfolios through an excessive allocation of resources to domestic equities (home bias). This relies on the increased availability of information and knowledge about this type of equities, that become more familiar to the investors. Also, the saliency of news referring to investments in foreign assets (that makes them more available) appears positively related to investors' willingness to purchase them (Shefrin (2002), pp. 187-188).
Another example articulates on the remark of Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) that investors lean towards attributing an excessive importance to private information. Mostly, this is overconfidently interpreted and highly trusted in comparison to public information (i.e. its accuracy is viewed to be higher than in reality). The psychologic mechanism underlying this phenomenon is simple: the intensive processing of private information gives rise to a higher availability, therefore to a more facile retrieval from memory and an overweight of the relevance of this type of information.

◇ *Representativeness* - indicates the incorrect assignment of an object to a certain class of objects on the basis of a badly or insufficiently defined similarity.

According to the original definition given in Kahneman and Tversky (1974), p. 431, representativeness comes into play when "the probability of an uncertain event, or a sample, is evaluated by the degree to which it is: (i) similar in essential properties to its parent population; and (ii) reflects the salient features of the process by which it is generated". Tversky and Kahneman (1982), p. 87, extend this definition suggesting that representativeness can rely on: "(1) a value and a distribution, (2) an instance and a category, (3) a sample and a population, (4) an effect and a cause. In all four cases, representativeness expresses the degree of correspondence between [...]" some instance/event and a

process/model.
However, Gigenrenzer et al. (1999) challenge these definitions by reason of conceptual vagueness. In addition, further studies point out the potential shown by different factors (such as situational transparency, degree of statistical sophistication, ability differences, or the perceived abstraction grad of the problem) in order to confine the sensitivity of people judgments to the use of heuristics in general (and of representativeness in particular).
In response to these findings, Kahneman and Frederick (2002) formulate a wider definition of representativeness which, in brief, centers on the idea that the use of this heuristic facilitates solving difficult tasks by converting them into more simple ones. They distinguish between: a judgment *of* representativeness (i.e. of what is prototypical for a class, population or distribution) and a judgment *by* representativeness (that relies on the degree of similarity between the outcome and the prototype). Furthermore, Kahneman and Frederick underline the interaction of two different cognitive systems that come into play when people make judgments: System 1 (which is spontaneous, fast, and intuitive) and System 2 (which is reflective, effortful, and slower). The failure of System 2 to permanently monitor and control System 1 results in the application of the simplifying rules generated by the latter, such as heuristics.

In sum, representativeness should not be understood as a failure of the human reasoning system, but simply as a (naturally employed) alternative to estimate probabilities. It helps in finding solutions for situations when objective probabilities cannot be calculated and for certain types of tasks (such as in case of unimodal, symmetrical distributions) it can even lead to optimal solutions (which are in addition faster and less elaborate), Teigen (2004).

With respect to financial markets, representativeness can explain the so-called positive feedback trading (the tendency of investors to buy recently higher priced assets) (Barberis and Thaler (2003)). Considering the (high) value of past returns representative, investors mistakenly extrapolate this positive evolution in the future.
Analogously, momentum trading (the buy of current winners and sell of current losers) which represents a favorite investment strategy of fund managers (Grinblatt, Titman, and Wermers (1995)), can be motivated by the tendency to mistake representativeness of past results for the likelihood of future prospects.
Also, the winner-loser effect documented by De Bondt and Thaler (1985, 1987, 1990) (the past losers perform much better than past winners, where both the past and future performance are measured over a period of three years) relies on the representativeness assigned to past returns for the permanent price evolution. In fact, this effect is more complex: at very short horizons (one month), Lehman (1990) documents an overreaction (investors overstate the probability of returns pattern continuation), while for middle-term periods (between three months and one year) investors appear to underreact (Jegadeesh and Titman (1993)).
Moreover, representativeness can entail to contrary reactions, such as the extrapolation of past trends (as documented by De Bondt (1993), which appears to frequently affect individual investors) or the gambler's fallacy (financial analysts inappropriately expect mean-reversions, i.e. reversals in the price evolution to occur more frequently than in reality) (Shefrin (2000)). What happens is that past trends (for trend followers) and reversals

(in case of gambler's fallacy) are considered to be representative for future evolutions.

◇ *Anchoring effect* - takes into account the influence of previously presented values on further judgments.

This effect proves to be extremely pervasive, robust (with respect to anchoring values, expertise and motivation), and persistent in time. Theoretical research suggests four causes for this phenomenon of assimilation with the anchor: (i)insufficient adjustment (people start forming judgments from an initial value provided by the anchor and adjust their estimations in order to reach a final answer; however, this process of adjustment mostly stops too early, at the boundary of the region of acceptable estimate values; this makes the reached solution to lie closer to the anchor; yet, insufficient adjustment can occur only for implausible anchors),(ii) conversational inferences (consisting in the use of implicit rules of natural conversations to standardized situations, when the anchor value is considered to be relevant), (iii) numerical priming (according to which there exists only one determinant of anchoring, the anchor value, while the context or judgmental operations involved are irrelevant; however, this theory cannot explain the influence of the semantic content or the persistence in time), and (iv)mechanisms of selective accessibility (under the terms of which anchoring has a semantic nature, representing a knowledge accessibility effect). With respect to the way it takes place, anchoring develops in two stages: the anchor selection (which is carried on the basis of accessibility, of relevance, or due to an insufficient adjustment process, so that the anchor is related to the features of the target), and the comparison to the target (which implies complex hypothesis-testing processes), Mussweiler, Englich, and Strack (2004).

In financial markets, anchoring provides a plausible explanation for the disposition effect documented by Shefrin and Statman (1985) (the predisposition of investors to sell winning stocks in their portfolios too early and hold losing ones too long). In other words, the effect addresses the reluctance to sell assets at a loss relative to the purchasing price, which obviously works as an anchor for the subjective perception of gains of losses. The anchor enables a mental delimitation between gains and losses (as in Kanehman and Tversky's prospect theory). The reluctance to losses (loss aversion) based on the fear to experience regret, enhanced by the hindsight bias (described below), gives eventually rise to the disposition effect.

A possible application of these three basic heuristics by illusionary traders consists in repeatedly sending misleading information meant to initiate trade in a certain direction (e.g. illusionary traders proceed to repeated purchase of a stock in volumes or at prices that call the attention of other investors). Thus, the generated signals can be perceived as representative and mistaken for relevant private information (pointing at a good investment). The price of the illusionary transactions can also turn to an anchor for further purchases of other investors. In fact, this hypothetical example finds support in praxis in the context of close-end funds. Hanley, Lee, and Seguin (1996) stress that fund managers usually support the inflated initial fund price for a while, which makes the fund to trade at a premium of around 10% in the first 4 months (Shefrin (2000)).

Apart of the afore mentioned basic heuristics introduce by Kahneman and Tversky there are other important illusions of judgement which influence financial decision making:

◇ *Validity effect* - points out the possibility to increase the perceived correctness (validity) of information by means of repeated presentation.

The validity effect may represent an automatic phenomenon, given that it illustrates a cognitive skill which relies on recognition memory which shows a limited development in time, so that, after increasing up to a certain age, recognition turns into a spontaneous process.

The validity effect was shown to occur equally for originally true or false statements of fact and of opinion. Moreover, familiarity with certain information creates the false impression of knowledge. Also, the belief that the information has been already heard, as well as the increased expertise render information to be considered more valid. (Renner (2004).)

As financial example, it is well-known (Shefrin (2000)) that investors manifest undue confidence in different indicators of the so-called market sentiment (such as the Bullish Sentiment Index or different technical indicators of this type), this in spite of clear evidence against their pertinence as forecast tools (Solt and Statman (1988), Clarke and Statman (1998)). Consequently, in the virtue of validity and mere exposure effects (see below), constructing and maintaining the public focuss on such "financial forecast instruments" can serve to manipulate public opinion.

◇ *Mere exposure effect* - refers to the increase in valence of information as a consequence of its repeated presentation.

Individual experiments and meta-analytic reviews attempt to inquire for the impact of three different categories of variables on the mere exposure effect: stimulus variables (e.g. while the stimulus type appears to exhibit no significant influence, complex stimuli entail stronger exposure effects), exposure variables (e.g. the liking of a stimulus shows a peak at 5-10 repeated exposures, heterogenous presentation sequences yield to a more intense exposure effect than homogenous ones, and the magnitude of the impact decreases with the exposure duration, but increases with the delay between exposure and rating), and participant variables (e.g. stimulus awareness appears to inhibit the mere exposure effect, the repeated imagination of stimuli reaches comparable effects as the repeated real exposure, while boredom and evaluation apprehension undermine this cognitive illusion).

The mechanisms underlying the mere exposure effect can be ascribed to a twofold process: a first one, affect-based (hence fast and reflexive, which serves to encode the stimulus attributes), and a second one, deliberate cognitive (thus more controlled, which helps to form mental representation of the stimulus). This conclusion summarizes the theoretical arguments of several theoretical approaches, such as: the arousal model of Berlyne (1970) (according to which familiarity to a stimulus is inversely related to the level of generated physiological arousal), the nonspecific activation model of Mandler, Nakamura, and Van Zandt (1987) (which posits that the mere exposure effect originates in the activation of previous mental representations of stimuli), the two-factor model of Stang (1974) (contending the interaction of two processes interact in order to produce the mere exposure effect: learning, which increases liking for a stimulus at lower exposure frequencies, and boredom, which entails the decrease of liking for higher frequencies of exposure), the perceptual fluency/attributional model of Bornstein and D'Agostino (1992, 1994) (which argues that perceptual fluency is falsely attributed to the familiarization to, thus liking of a stimulus), and the affective primacy model of Zajonc (1980) (which claims that the mere exposure effect represents but a pure affective response). (Bornstein and Craver-Lemley (2004).)

◇ *Overconfidence* - indicates excessive faith in the accuracy of one's judgments, where accuracy is measured either in terms of probability or of confidence intervals. Therefore, overconfident subjects can be on the one hand miscalibrated when they estimate absolute or average probabilities, i.e. they consider their answers to be correct (incorrect) with a higher (lower) probability than in reality. On the other hand, they can assign too narrow confidence intervals to estimates of quantities, i.e. they think their estimates are closer to the true value than de facto. The contrary phenomenon of insufficient confidence is denoted as *underconfidence* or *conservatism*. With respect to companies, the overconfidence about own competencies is referred as *hubris* (Shefrin (2000), p. 227).

The majority of empirical studies with respect to miscalibration stresses the existence of various effects that can be connected to the notion of overconfidence: the overconfidence effect (stating that the mean confidence in the accuracy of a choice or statement exceeds the correct percentage), the hard-easy effect (an increase in the difficulty of items directly reflects in the level of overconfidence), the dependence on the sampling procedure (in representative samples, the poor calibration exhibits a lower magnitude), the base-rate effect (subjects do not adjust their confidence with respect to the variation of base-rates), the confidence-frequency effect (confidence is significantly higher than frequency estimates), the expertise effect (expertise can alleviate poor calibration results), betting (subjects bet more willingly against the experimenter in laboratory settings, while in natural settings they appear to be almost perfectly calibrated), simultaneous conservatism and overconfidence (depending on the situation, people prove to be both conservative, thus to ascribe a higher importance to prior information, and overconfident, thus to trust rather new evidence), format dependence, and the independence of underconfidence and error between participants in tasks that require sensory discrimination.

The original heuristics and biases programme developed by Kahneman and Tversky in 1970-1980 considers overconfidence as a sign of irrationality and motivates it by means of anchoring and adjustment heuristics, or of the confirmation bias. Afterwards, Ferrell and McGoey (1980) formulate a formalized approach called the signal-detection theory, according to which confidences are conceptualized as functions of the distributions of true and false statements. Later on, ecological models (McClelland and Bolger (1994)) raised from the theory of probabilistic mental models of Gigerenzer, Hoffrage and Kleiboelting (1991) and the one of Justin (1994), emphasize the distorting role of the item-selection procedures used by experimenters (e.g. not representative item-samples) on the (ecological) validity of cues, which leads to wrong (i.e. overconfident) choices. Erev, Wallsten, and Budescu (1994) and Pfeiffer (1994) stress the role of response error in generating underconfidence. More recent approaches of Bjoerkman, Juslin, or Olsson combine the mismatch between cue validities for a sample and the population and the unsystematic response error. Dougherty (2000) assumes that frequency information which generates the above mentioned errors is not stored separately from memory-trace information, so that error does not further pertains to response, but to the retrieval of information. The sensory sampling model of Juslin and Olsson (1997) suggests that people make decisions on the basis of the proportion of short-term impressions and then identify this proportion as confidence. (cf. Hoffrage (2004).)

A financial example is provided by the empirical and theoretical findings of Barber and Odean (2000, 2001) concerning the tendency of investors to trade more and to earn lower returns on average. The rationale for this phenomenon is the overconfidence in the own abilities and the accuracy of own information.
Furthermore, analysts appear to react conservatively when they do not revise their forecasts quickly enough in order to accommodate new evidence from earnings announcements (Shefrin (2000)).
A more complex application referring to the combined impact of different cognitive illusions on asset prices relates to an observed market phenomenon which consists in the use of momentum strategies at intermediate term coupled with a post-earnings-announcement drift (underreaction of financial analysts to earnings information and of prices to analysts' forecasts) on longer horizons (Shefrin (2000)). Several theoretical models were developed in order to explain this intricate pattern. First, Barberis, Shleifer, and Vishny (1998) bear on the interaction of conservatism (which hampers in the first place the incorporation of surprising new evidence in the investors' strategies) and representativeness (which subsequently entails an overreaction to repeated news, i.e. a trend-betting strategy). Second, the (already mentioned) model of Daniel, Hirshleifer, and Subrahmanyam (1998) pertains to the combination of overconfidence and self-attribution (which makes people to assign successes to own skills and blame failures on bad luck or on others)[5] which makes the investors to overreact to own information and underreact to public information. Third, Hong, Lim, and Stein (1999) draw upon informational asymmetries and cognitive limitations which slow down the diffusion of information among investors geenrating the twofold pattern under discussion.

◇ *Pollyanna principle* - states that pleasant items are typically more accurately and efficiently processed than unpleasant or neutral ones. In addition, the judgments about various people, events, situations, objects are mostly inflated. In economic literature, the same notion is often referred as *optimism* (Barberis and Thaler (2003), p. 1064).

In memory, people appear to be inclined to remember positive events. Also, memories tend to grow more positive over time, and the self-esteem, as well as the current mood are directly related to the valence of recalled items (e.g. people with high self-esteem or in a positive mood remember rather pleasant events). Regarding judgments, people form positive opinion about the quality of their lives and hold inflated beliefs about their own abilities and the attributes of other (yet unknown) members of their own group. (cf. Matlin (2004).)

According to Shefrin (2000), both investors and managers suffer from excessive optimism about the future prospects of IPOs.

Illusionary traders can exploit the Pollyanna principle and the overconfidence of other market participants in a bullish market by sending positive signals referring to a certain stock. Given that people are known to be in a good mood and to pay special attention to positive news when the market evolution is positive, the illusionary signals will yield inflated prices.

[5]Self-attribution can be explained through the Pollyanna illusion (see below).

5.2.3 Illusions of memory

A third category of cognitive illusions focusses on memories and how their accuracy can be altered by different factors. Several phenomena are in line with these criteria:

- *Moses illusion* - defines the tendency to overlook semantic distortions in statements or questions.

  Several theoretical explanations account for the emergence of this effect: the cooperative principle (states that the distortion is noticed but attributed to an involuntary mistake of the speaker and ignored), imperfect encoding (the distortion is simply ignored because people do not carefully listen to or read the information), imperfect memory retrieval (the proposition is correctly heard or read but only incomplete information is recalled in order to detect the distortion), and imperfect matching of the question terms to memory structures (due to semantic or phonetic similarity between the distorted and the original term). While none of the first three of these assertions allows for all documented aspects of the Moses illusion, the latter provides a solid basis for understanding it. (cf. Park and Reder (2004).)

  In financial markets, small changes in the message content of news may pass unobserved by the large public in the first place. This provides to attentive illusionary traders an advantageous head start they can benefit from.

- *Associative memory illusion* - refers to the false recall or recognition of never presented information.

  The Deese-Roediger-McDermott (DRM) paradigm (developed in Roediger and McDermott (1995) after an idea of Deese (1959)) tests the recognition and remembering of a nonrepresentative target word associated with a previously presented list of words. This list shows similar recall levels to the veridical memories of the words in the list. The procedure generates strong and robust associative memory illusions.

  Processes that underlie the DRM findings can be categorized as: association-based (according to which associations activate a pre-existing mental representation of the critical non-presented word that causes false recognition or recall), and similarity-based (the semantic similarity between the critical item and the other list items is considered as main cause of the false remembering; this relies on the specificity of encoding particular and general information related to an item). Both associative activation and semantic similarity appear to play a role in generating associative memory illusions. Another explanation for associative memory illusions draws back on the idea that, in order to imagine the presentation of the critical word, highly fluent mental processes are developed which facilitates its false acceptation as one of the words in the list.

  The DRM effect appears to respond at different procedures meant to attenuate or eliminate it. These procedures are referred as reality monitoring and are based upon editing processes. They focuss either on presentation manipulations without consequences on the associative activation or semantic similarity (such as presentation format or presentation modality), or on manipulations that should increase associativity or similarity but decrease false remembering (such as increasing the number of presentations of the list or slowing presentation rate). (cf. Roediger and Gallo (2004).)

Illusionary traders can exploit the DRM effect in that they attempt to draw public attention on various elements of positive or negative valence that can be easily associated with a stock or a trade decision regarding this stock (such as past performance, money made by well reputed market participants as a result of trading the stock, news about the company, or even more general information such as indicators of market evolution). The associative illusions generated this way facilitate the transfer of the perceived element valence on the stock, hence entail a directional reaction of the public that can be profitably accommodated by illusionary traders.

◇ *Effects of labelling* - develop when labels systematically influence the judgment or recall of a stimulus.

Labelling effects have been found with respect to the recall of visual forms and colors, abut also the judgment of speed, taste, and odor. They appear to arise even when labels are self-generated. However, labelling effects proved to be rather fragile and depend on the complexity of the analyzed material. In the same context, the notion of verbal overshadowing introduced by Schooler and Engstler-Schooler (1990) points out the deterioration of memories of visual stimuli (such as faces or colors) as a consequence of verbal self-descriptions (labels).

Due to the fact that labels provide helpful information in order to decrease the subjective ambiguity or uncertainty, labelling can be understood as a suggestive process. Accordingly, labelling drive the representation of the stimulus (attribution of meaning) in a certain direction. It appears that labels can influence the memory representation of the stimulus itself, as formed in the encoding phase, but they can also serve as cues during recall. (cf. Pohl (2004b).)

In financial markets, valuation statements related to a stock made by well-reputed persons and/or repeatedly presented to public can serve as label (anchor) for estimating future stock performance (e.g. especially for new issues the public is not yet familiar with).

◇ *Misinformation effect* - suggests the capacity of post-event misleading information to deteriorate the accuracy of remembering the original event.

This effect proves to be robust and to affect memory in an extensive way, e.g. by changing the existing information, inhibiting previous stored one, or even adding new information (from small details to entire false events). The processes responsible for all misinformation effects found are various and complex. In principle, the mechanism consists in that misleading information yields to modifications in the mental schema formed in order to represent an event and accessed to the purpose of recalling it. One possible explanation for the efficiency of this mechanism relates to familiarity, a feeling experienced when people fluently process an event whose origin can be mistakenly attributed to past experience.

To date, there exist no reliable means to distinguish true from false memories. However, we know that it is possible to alter a true memory or to plant a false one with either positive or negative consequences. (cf. Pickrell, Bernstein, and Loftus (2004).)

The misinformation effect (especially the implantation of false memories) can be of high interest with respect to the activation of financial illusions. Illusionary traders can benefit on changes in memory induced by post-event news (either exogenous or intentionally created by themselves), in that they accommodate with the false trade positions taken by the investors who fell prey to this illusion.

◇ *Hindsight bias (knew-it-along effect)* - denotes the tendency to overestimate a-posteriori (in hindsight) the foresight knowledge. Formally, the hindsight bias arises when the posterior estimate lies closer to the true solution than the prior estimate.

This effect proves to be very stable and reluctant to every intentionally attenuation attempt. Moreover, the underlying mechanisms are still not very well explained. On the one hand, it can result from the inability to ignore the solution. In this context, Fischhoff (1975) asserts the immediate assimilation of the solution in the knowledge base which biases it towards the solution. Tversky and Kahneman (1974) claim that solution may function as an anchor where the reconstruction of foresight knowledge starts from, but the reconstruction process is biased, given that it mostly stops too early, when a satisfactory threshold is met. Hell et al. (1988) argue that the trace strength of the solution relative to that of the original estimate is positively related to the intensity of the hindsight bias. The biased-reconstruction theory of Stahlberg and Maas (1998) contends that the presentation of the solution does not entail changes in the knowledge but affects the reconstruction in that it acts as a retrieval cue. On the other hand, Pohl, Eisenhauer, and Hardt (2003) develop the Selective Activation and Reconstructive Anchoring (SARA)-model according to which new images (viewed as knowledge units) interfere with the matrix of existing ones. The images in this mental matrix are differently activated and sampled in order to retrieve original information. The hindsight bias is assumed to emerge as a result of: selective activation (when the associations with the solution set become stronger which generates a higher likelihood of finding), biased sampling (towards solution-related images), or both of them.

While metacognitions, such as surprise in front of the (plausible) solution (which prevents its integration into the knowledge set or its use as retrieval cue), can hamper the hindsight bias, motivational factors and individual differences appear to play only minor roles as possible sources of influence. (cf. Pohl (2004c).)

Last but not least, the hindsight bias hides the substantial risk that, feeling wiser after knowing the results might render people overly optimistic about own knowledge and abilities. In conjunction with overconfidence, this can dramatically bias future decisions and slower the learning process from past experiences.

◇ *Illusions of change or stability* - account for an inflated discrepancy or consistency, respectively, between past and present states.

The human memory appears to be based in great extent on current knowledge, beliefs and aims. Often, people do not recognize how much they have changed over time. They may be inclined to see themselves as coherent and stable over time, which may justify the illusion of stability. At the same time, they can also be motivated to perceive a change (mostly in the sense of improvement) in the self, which results in illusions of change. These two tendencies are not as contradictory as they may seem at first: people typically expect little change over short periods of time (or periods which are subjectively considered as such) and greater improvements over longer (perceived) periods. Thus, while recent selves directly reflect on the present self, more distant past can be recalled as being less favorable. Consequently, individual motivations determine the type of revision made by an individual. (cf. Wilson and Ross (2004).)

CHAPTER 6

Illusionary Finance and Trading Behavior

IN THIS CHAPTER we focus on the idea that one important aspect of financial markets is that there might exist traders that intentionally mislead other market participants by creating illusions in order to obtain a profit.

Based on the concept of illusionary finance introduced in chapter 4 and 5, we present an analysis of how illusions can be created and disseminated in financial markets based on certain psychological principles that explain agents' decisions under time pressure and polysemous signals. Furthermore, we develop a simple model that incorporates the illusions in the price formation process and using simulations, we show how illusions can be incorporated, directly or indirectly, in the expected prices of the traders.

6.1 Introduction

The efficient market hypothesis (EMH) (Fama (1970)) suggests that, at any time, prices fully and instantaneously reflect all available relevant information on a particular stock or market. The information contained in the prices also reflects the way in which investors perceive and interpret such information. Thus, no investor has an advantage in predicting the return on a stock price since no one has access to information not already available to everyone else. Accordingly, the EMH implies that it is impossible to "beat the market" because prices already incorporate and reflect all relevant information. More importantly, the EMH framework assumes the existence of rational agents. This assumption is characterized by two aspects. Firstly, the agents update their beliefs by correctly incorporating all relevant information of the current situation, as well as expectations about the future opportunities and risks. Secondly, they make choices that are normatively acceptable, i.e., consistent with Savage's notion of subjective expected utility. However, in reality people's decisions arguably often express affective evaluation (attitudes) that do not conform to the logic of economic rationality. Moreover, most judgements and most choices are made intuitively. In order to understand other important aspects that influence agents' decisions, one may need to understand some human psychological principles (Kahneman, Wakker, and Sarin (1997), Kahneman (2003))

As we have seen in the privious chapters (see chapter 1,2, 5 for further references), one area in which researchers have linked psychology with economics is behavioral finance, which provides explanations to well known market anomalies, such as: the stock market overreaction and underreaction (Daniel et al. (1998), Barberis, Shleifer, and Vishny (1998), and DeBondt and Thaler (1985)); the persistence of mispricing (DeLong, Shleifer, Summers and Waldman (1990); Shleifer andVishny (1997); the survival of overconfident traders in a competitive stock market(Hirshleifer and Luo (2001)); and the market inefficiencies that allow some individual skilled investors to earn abnormal profits (Coval, Hirshleifer, and Shumway (2002)). The explanation for these market anomalies brought from the psychological field are, for example, prospect theory, representativeness heuristic, conservatism, overconfidence, gambling behavior, and speculation. The behavioral finance literature shows some limits of the efficient market hypothesis when psychological aspects are taken into account.

In this chapter, we present an analysis of how illusions can be created and disseminated in stock markets. Our work is based on certain psychological aspects that explain some agents' decisions [1] under time pressure and polysemous signals[2], which have been introduced in chapers 1 and 5.

Illusionary finance studies how an agent can profit from other agents psychological biases, taking advantage of polysemous signals and time pressure. Illusionary finance is possible since agents cannot make fully-rational decisions all the time, at least in the economic sense. Instead, they make their decisions based on "bounded rationality" (Kahneman (2003)). The judgements that people express, the actions that they take, and the mistakes that they make depend on the monitoring and corrective functions of reasoning, and on the impressions and tendencies generated by their intuitions.

The rest of the chapter is organized as follows: Section 6.2 explains the concept of illusionary finance and how to distinguish it from noise. Section 6.3, gives the intuition on the creation of illusions in stocks markets and their influence on the price formation process. Section 6.4 explain the simulation results and finally and Section 6.5 concludes and provides an outlook for future research.

6.2 Illusionary finance

In this section, we show how illusionary finance tricks financial markets. The psychological aspects discussed in the previous chapter allow us to introduce the illusionary mechanism that

[1]Heuristics and biases.

[2]Polysemous signals are defined as indicators that have multiple interpretations. For more information about the semantic concept of information and polysemous signals, please refer to the works of Saussure (1967) and Dretske (1981)

can be created in the stock market and embedded in the information set as if it were relevant information and not an illusion. This illusionary mechanism is related to behavioral finance given that in behavioral finance literature, market anomalies are extensively reported. Coval, Hirshleifer, and Shumway (2002) examine the fact that there are individual investors capable of beating the market, which implies the violation of the semi-strong form market efficiency. They conclude by an interesting question: are the large brokerage companies aware of the value of the information contained in their customers' trades? In our framework, the fact that there are agents that are not aware of the relevance of the information contained in trades means that it is possible to integrate an illusion into the agents' information set.

It is also important to clarify how the illusionary trader takes advantage of the psychological bias of the other market participants.[3] Firstly, he sends a polysemous signal with the intention to create a financial illusion for the other market participants. Secondly, this sign is perceived by other traders. According to the perception of the signal, the type of trader (information trader, noise trader[4], and the external circumstances (bearish or bullish market) including the time constraint to make decisions, the signal might be considered as information or noise. Following Thaler (1993) and Black (1986), we can define noise as the opposite of news. Information traders trade on the basis of news (facts, forecasts, etc.). Noise traders trade randomly and not based on information.[5] Even though the information sets of the information traders and the noise traders are different, information traders might consider the illusion as noise or as information. If they consider the illusion simply as noise, they do not use it in their information set and the illusion has no effect. On the other hand, if they consider this illusion as information, they consider it in their information set. We call this sub-group of traders **believers**.

The desired impact of the illusion depends on many factors that the illusionary trader cannot control but that he can use when the opportunity shows up. The reason why information traders trade on illusions is simple: they consider the perceived illusion not as noise but as information. This is possible in stock markets because there is so much noise in the market that they do not know if they are trading on noise or on information, and when deciding about what is information, they can make mistakes. The illusionary trader takes advantage of this situation to incorporate the illusion in the information set of certain traders with the clear objective of profiting from this situation. The fact that believers take into account illusions may not be completely irrational. Even if they figure out that some information is indeed an illusion, it may nevertheless be rational to take the illusion into account, as long as they believe that there are other believers in the market who take the illusion into account. If no one takes the illusion into account and everyone rationally anticipates that, then it is a best reply not to take it into account. However, if everyone takes the illusion into account and again everyone rationally anticipates that, then it is a best reply to take it into account.

Black (1986) presented a paper describing and explaining what noise is in stock markets. He described an information trader as someone who has the information or insights on individual firms and a noise trader as someone who trades on something else. Black (1986) argues that noise makes financial markets possible, but also makes them imperfect. In this chapter, we

[3]Illusionary traders differ from speculators who are those traders that profit from information they have about future prices (Harris 2003), while illusionary traders create illusions by sending polysemous signals.

[4]As in Black (1986)

[5] For example they trade to match their own liquidity requirements because of inherited money or because they want to buy a new car or house.

add a new type of traders into financial markets called illusionary traders. These traders send polysemous signals to the market and expect to profit from this information.

According to Black (1986), information traders take advantage from their positions in trading with noise traders because they have some relevant information about individual firms. With a lot of noise the information traders are more profitable, simply because prices have more noise in them. However, the information traders can never be sure that they are trading on information rather than noise. They can always think that the information they have received has already been reflected in prices, and then trading on this kind of information will be just like trading on noise. When traders face a lot of information arriving at the market, as long as we are talking about potentially relevant information, the problem is that there are many possibilities to be ruled out before they can be sure to have determined which information is relevant. In short, the more possibilities of potential relevant information, the harder it is to find out what is relevant, and this fact can be used by illusionary traders.

In Black (1986), the prices in the market reflect both the information that the information traders trade on and the noise that noise traders trade on. In the illusionary finance context, we add to this price formation setup the illusion that the believers trade on.

Illusionary traders add misleading signals (illusions) to take advantage from the traders that we call believers. The group of believers can be either information traders or noise traders.

One should note that Black (1986) did not consider traders that trade on illusions; he only considered the noise traders explaining that noise traders are necessary for financial markets to be operative. Illusionary traders are not necessary, but they may exist. Moreover, recent financial frenzies and scandals cannot be the result of only noise. Our contribution is to introduce the concept of illusionary finance, which we think is more realistic than considering only noise.

6.3 Simulations

In this chapter our intention is to show using simulation techniques that it is possible to create illusions that translate into positive returns. We argue that illusions imply superior information for the traders who create them because they are the only ones that know about them. These traders use this superior information for their own interest. We do not present a theoretical model of illusions. This and some other ideas presented hereafter are left as open questions for future research.

Even though the existence of a market-maker system is not a necessary condition in our simulation techniques, in the United States, the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX), have a single exchange member, known as the "specialist," that acts as the official market maker for a given security while the NASDAQ Stock Exchange, employ several competing official market makers in a security. As we will point out in the next section, the data that will be used comes from those exchanges. Thus, we believe it is more adequate to use a market-maker system in our simulations. Following Glosten (1994), we define two kinds of traders interacting in the stock markets: patient and impatient traders. Impatient traders are the traders who submit market orders (MO) and patient traders submit limit orders (LO). The reasons for submitting MO instead of LO can be due to private information or due to liquidity reasons.

In this chapter the focus is going to be on the impatient traders and we are going to assume that the book, maintained by the market-maker, is exogenous and spontaneously refilled by the patient traders. We also classify impatient traders into three types: (1) *Information traders*, who neither believe nor incorporate the illusion in their decision sets. (2) *Believers*, who believe in the illusion and incorporate it in their expectations about future prices. (3) *Noise traders* who consider in their expectations "relevant" and "irrelevant" information without distinguishing between them.

We define N_t as the **proportion** of impatient traders at time t (number of impatient traders/total number of traders), and M_t the proportion of patient traders at time t (number of patient traders/total number of traders).[6] Thus, $N_t + M_t = 1$.

We assume that each trader can make a single trade each period, hence one trader is equivalent to one trade.

In our simulation we focus on the proportion of impatient traders (information traders, believers and noise traders) which, by assumption, is equal to the number of trades. We assume that the distribution of impatient traders (N_t) is not affected by the illusions. What is affected however, is the proportion of these traders, i.e. some information traders become believers. This is an important assumption in the simulation.

However, special care must be taken with respect to the timing of illusions in the market. An illusion is sent to the market at time t.[7] There are some information traders who do not consider it in their information set; however, in their information set of the next period ($t+1$), they will consider the prices at time t. Since prices at time t already contain the illusion, these information traders are indirectly influenced by in the illusion.

In our framework the information traders (INF) at time $t-1$ forecast the asset price for time t simply as:

$$E[P_t|\mathcal{F}_{t-1}^{INF}] = \bar{P}_t^{INF} = \frac{1}{n}\sum_{i=1}^{n} P_{t-i} \tag{6.1}$$

where $\bar{P}_t^{INF}$ is their expected price at t given their information set ($\mathcal{F}_{t-1}^{INF}$) at $t-1$. The information set at $t-1$ contains only information about past prices. P_{t-i} are past prices. n is the number of past price realizations that are taken into account to determine the expected prices.

We assume that noise traders (NT) simply make random price expectations:[8]

$$\bar{P}_t^{NT} = \varepsilon_t \tag{6.2}$$

Believers' (B) expected prices are:

$$E[P_t|\mathcal{F}_{t-1}^{B}] = \bar{P}_t^{B} = \bar{P}_t^{INF}(1 + I_t) \tag{6.3}$$

[6] We assume that there is a given fixed number of traders during the whole simulation exercise.

[7] This means that the illusion is available only at time t and is incorporated into prices at the same time.

[8] We can also assume that the noise traders set their expected prices equal to a mean, which is the same for all market participants, plus a random zero-mean noise.

where $\bar{P}_t^B$ is the believers' expected price for time t given their information set $\mathcal{F}_{t-1}^B$, and I_t is the impact of the illusions on the expected prices. I_t can depend on many different psychological or economic factors. Moreover, the functional form of this relation can be of many different forms.[9] In the present simulation, I_t is given by:

$$I_t = \psi(N_{t-1} + \eta_{t-1})\, \theta\, \xi_{t-1} \tag{6.4}$$

where $\psi(\cdot)$=+1 or -1 is the desired sign of the illusion, N_{t-1} is the proportion of impatient trades that occurred at time $t-1$, η_{t-1} is an additional proportion of trades that only appears if the market is in a bear period,[10] θ is the illusionary trader size, an approximation of the market power that can differ across traders, and ξ_{t-1} represents the quality of the illusion. In principle we consider this quality to be a random variable with uniform distribution on $[0, 1]$, but that can also be modeled differently. We use such randomness because there is no reason to believe that all believers are going to be affected in the same way by different types of news or illusions. One can think of it as an average of the impact of the illusion on the believers.

Knowing the proportion N_t of trades at time t (an exogenous variable in the present setting), we can define the composition of the trades in terms of proportions. We assume that the proportion of believers at time t (N_t^B) is given by:

$$N_t^B = \delta N_t \tag{6.5}$$

with $0 \leq \delta \leq 1$ such that $0 \leq N_t^B \leq N_t$. Once we know N_t^B we let the proportion of information traders (N_t^{INF}) follow a uniform distribution on the interval $[0, N_t - N_t^B]$. Finally, the proportion of noise traders is simply $N_t^{NT} = 1 - N_t^B - N_t^{INF}$. Note that in order to obtain N_t^{NT} we subtract from 1 and not from N_t. This implies that the totality of the market participate in the price formation process. Moreover, with this structure, even if they are considered as exogenous, the patient traders participate randomly in the price formation process. Hence, this is a flexible structure which allows us to simulate different scenarios like the one in which the market is composed mainly by information traders. For this, we simply need to fix $\alpha \leq N_t^{INF} \leq N_t$ and $0 \leq N_t^B \leq N_t - N_t^{INF}$, where $\alpha \geq 0$ represents the minimum proportion of information traders present in the market.

When the market is in a bear period, we want to capture the leverage effect observed empirically. We define as *bear-believers* the traders who behave as information traders in regular times (bull markets) but become believers in bear markets. Their proportion (conditioned on the bear market) (η_t) can be defined in many different ways,[11] for simplicity and to facilitate the exposition, we define it by:

$$\eta_t = N_t^B\, N_t^{INF} \tag{6.6}$$

i.e., η_t is the fraction of the proportion of information traders who act as believers in bear markets.

[9] This is left for future research. Moreover, we assume that sending an illusion is costless.

[10] With this we are able to capture the leverage effect proposed in **?**, i.e. that negative news affect market participants more than positive ones.

[11] We can think of defining it as: $\eta_t = \pi\, N_t^{INF}$, where π is a uniform random variable on $[0, 1]$.

In this simple setup, we do not know anything about traders' demands given their price expectations. Moreover, we do not know what their decision would be (buy, sell or not to trade), according to their preferences for a given price expectation.[12] Thus, we assume that the actual price is a weighted average of the price expectation of the different kind of traders. According to these, the price of the asset at time t is:

$$P_t = N_t^{INF}(1 - N_t^B D_t)\bar{P}_t^{INF} + N_t^B(1 + N_t^{INF} D_t)\bar{P}_t^B + N_t^{NT}\varepsilon_t \tag{6.7}$$

where D_t is a dummy variable that takes the value of 1 if we are in a bear market and 0 otherwise. With this specification we do not assume that the illusion is the only noise present in the market. The third term on the right-hand side of equation (6.7) captures this idea and helps the simulations to be more realistic and less controlled.

In order to understand the dynamics of the proposed simulation let us show what happens during the first two periods of trading. At time $t-1$ all kinds of traders fix their strategies. The price at t according to Equation (6.7) has a component driven by the expectations of the information traders ($\bar{P}_t^{INF}$), the expectation of the believers $\bar{P}_t^B$, and the expectation of the noise traders (ε_t). At time t traders forecast the price for $t+1$. Here one can observe that for the information traders the expected price for $t+1$ is:

$$\begin{aligned}
\bar{P}_{t+1}^{INF} &= \frac{1}{n}\sum_{i=1}^{n-1} P_{t-i} + \frac{P_t}{n} \\
&= \frac{1}{n}\sum_{i=1}^{n-1} P_{t-i} + \frac{N_t^{INF}(1 - N_t^B D_t)\bar{P}_t^{INF} + N_t^B(1 + N_t^{INF} D_t)\bar{P}_t^B + N_t^{NT}\varepsilon_t}{n}
\end{aligned} \tag{6.8}$$

Clearly the second term of the sum incorporates the illusion that influences indirectly the information traders. In the case of the believers, as soon as the direct effect of the illusion (I_t) disappears, their expectation converges to the information traders' expectations (see equation (6.3)).

6.4 Results

For the starting values of our simulations we use observed features from the IBM stock: the number of trades and the stock prices over 5-minute intervals. The data was from January 1st 1998 to March 31st 1998. The historical prices are given by the average mid-quote during the time interval. The data we use was taken from the Trades and Quotes (TAQ) dataset, produced by the New York Stock Exchange (NYSE). This data set contains every trade and quote posted on the NYSE, the American Stock Exchange and the NASDAQ National Market System for all securities listed on NYSE. Table 6.1 presents the descriptive statistics of this data set.

[12] This is an appealing topic for future research.

Table 6.1: Descriptive statistics

	trades	prices
Mean	16.06	64.54
Std.Dev.	7.43	3.41
Maximum	54	74.38
Minimum	0	59.38

Descriptive statistics for the number of trades and mid-quote prices (in USD). The number of observations is 4636 and correspond to 76 5-minute intervals for 61 trading days. The sample period goes from 01/01/98 to 31/03/98.

As stated in Section 6.3 we assume that the number of trades is not affected by the illusion, what changes is the composition of the different kind of traders. Moreover, we assume that:

- ◇ the number of trades follows a Poisson distribution with mean equal to the unconditional mean of the number of trades in 5-minute intervals of IBM (Table 6.1);
- ◇ the expected price of noise traders is assumed to follow a normal distribution with mean and variance equal to the historical mean and variance of the series;
- ◇ for the initial composition of the impatient traders, uniform random numbers are generated for each type: information traders, believers and noise traders;
- ◇ for the illusionary trader's size (θ), we chose it to be a uniform random variable in the interval $[0.01, 0.15]$, which represents a relative measure of the traders' market cap with respect to the total size of the traders actually intervening in the market;
- ◇ the market is bullish.

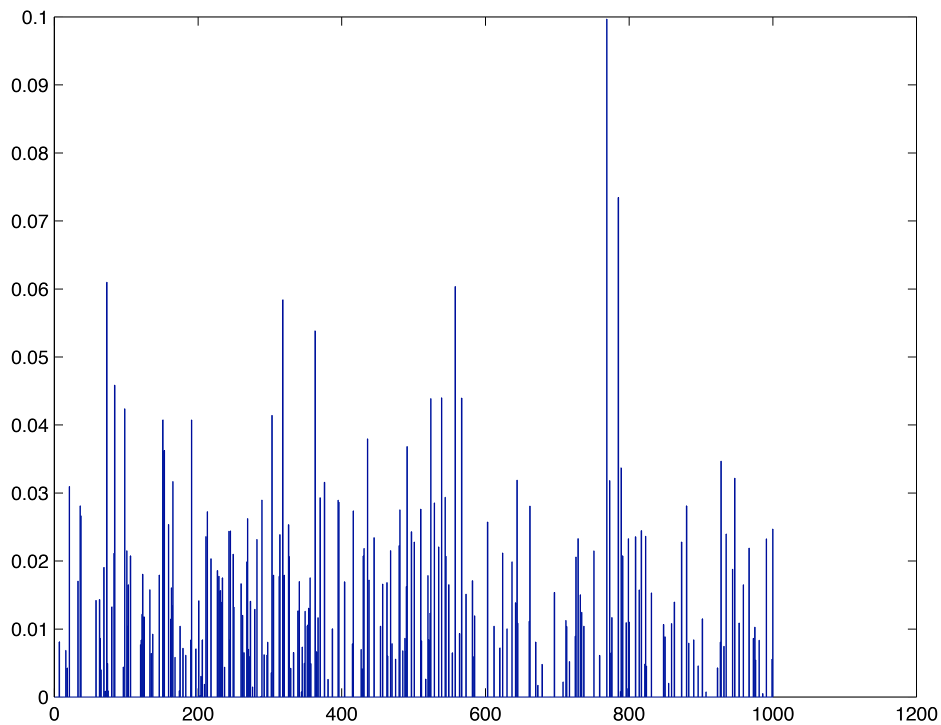
In order to determine the effect of the illusion, we assume that the illusionary traders expect a random effect of their illusion based on equation (6.4). If they send a positive illusion, they expect that prices go up. However, they also know that the believers will rapidly realize that the illusion is not relevant information and rapidly correct their expectations, forcing the prices to their normal level. Thus, they expect a fall of the prices in the next period. Their strategy in this case is simply to sell after the illusion and buy back the asset when the prices fall to their normal levels. However, it is important to note that given the randomness of the market, the prices might not follow their expectations. In these cases, they do the following:

- ◇ If the prices at $t + 1$ do not follow their expectations, given the illusion created at time t, they do nothing (no action).

◇ If the prices at $t+1$ follow their expectations, they sell (buy) the asset if they posted a positive (negative) illusion. If the prices at $t+2$ do not fall (rise), they wait for a certain period looking for a price that is simply equal to or smaller (bigger) than the price at which they sold (bought) in order to buy (sell) the asset.

Given the above explanations about the way the simulation is driven, we present the results of a simulation based on 1000 replications. The size of the trader in terms of his relative market capitalization is randomly selected from $[0.01, 0.15]$ in each replication, i.e., from a small to a large trader.

Figure 6.1 presents the results of applying the traders strategies described before. We can see that this trading strategy gives a positive payoff as a result of the illusion sent to the market. We see that the expected effect of the illusion is not always achieved, this is the reason why there is a big proportion of zeros (no action).



Unit monetary income (vertical axis) resulting of applying the trader's strategy given the illusion sent to the market. The number of simulations is 1000 (horizontal axis).

Figure 6.1: Traders strategy results

Table 6.2 presents some statistics of the payoffs obtained sending illusions to the market. One should note that of 1000 illusions, only 241 allow the illusionists to apply their strategies and to obtain a positive payoff. This situation happens because the illusion's impact on the prices is given by the believers expected prices, which by assumption are only a proportion of the impatient traders, making their influence very limited.

Table 6.2: Traders strategy results: some statistics

Period	**max**	**min**	**mean**	**std**	**sum**	**action**	**no action**
Bull	0,0997	0,0000	0,0040	0,0096	3,9634	241	759

This table present some results of the traders strategies given the illusions sent to the market. The results are presented in monetary units for a trade of a single share. "Action" refers to the number of times the expected traders' illusion has the desired impact on the market prices. "No action" refers to the number of times when the trader's illusion did not produce the desired effect and so the trader did not do anything.

Table 6.3 shows some statistics about the proportion of the different kind of traders that result as a consequence of illusions sent to the market. It also shows some statistics about the price expectations of the different traders. Looking at that table, one notices that the maximum proportion of impatient traders (traders who submit market orders) represents one quarter of the total market traders. From this group the information traders represent the majority. We can see that the impact of the illusion is very small, with a maximum of 8.99% and a minimum of zero (no impact).

By assumption the largest group of traders are the noise traders, which includes the proportion of patient traders who place their limit orders exogenously and randomly. Another interesting feature to observe is that the expected prices of the different type of traders are not very different. These results are coherent with the price movements observed in stock markets in which the prices cannot vary more than a certain level without triggering a market halt.

6.5 Conclusions

In this chapter we explore the concept of illusionary finance. Our analysis focus on how the illusions can be created and disseminated in stock markets. We expose in a market microstructure context, how a trader can profit from other agents psychological biases, taking advantage of polysemous signals and time pressure. Illusionary finance proves to be possible since agents cannot make fully-rational decisions all the time. Illusionary traders take advantage from the believers which can be either information traders or noise traders.

Illusionary traders are not necessary for markets to be operative (as information and noise traders) but they exist. Our contribution is thus to introduce the concept of illusionary finance, which is a realistic way to integrate the functioning of stock markets with psychological aspects of the traders.

An interesting conclusion derived from our simulation is, that even though information traders are skeptical about the illusions at time t, they end up indirectly including the illusion in their forecast of the next period after the illusion was created, showing once again the power the illusions have in financial markets.

In our study our intention was to show that financial illusions may exist in financial markets even it is difficult to detect them. A possible extension of our ideas is to develop a theoretical model of illusions in which the existence and survival of the illusionary trader can be shown. Another extension could be to develop a model which considers the impact of illusions on the patient traders, i.e. in the traders that submit limit orders.

Table 6.3: Illusions impact

Period: Bull	**max**	**min**	**mean**	**std**
Impatient traders (%)	0.2367	0.0233	0.1098	0.0256
Information traders(%)	0.1733	0.0003	0.0542	0.0279
Believers (%)	0.0899	0.0000	0.0015	0.0075
Noise traders (%)	0.9993	0.8062	0.9444	0.0281
Expected price information traders	60.0155	59.9468	59.9778	0.0214
Expected price believers	61.1454	58.5995	59.9787	0.0815
Expected price noise traders	60.0445	59.9177	59.9777	0.0236
Realized prices	60.0701	59.8519	59.9777	0.0236

This table present some results of the impact of the illusions on the proportion of believers and on the realized prices.

CHAPTER 7

Hopes and Beliefs in Financial Markets: Can Illusions Survive in the Long run?

In this final chapter we present a theoretical model based on the concept of illusionary finance presented in chapters 1, 5 and 6, characterizing markets as an evolutionary environment where ambiguity and uncertainty are common features.

In that context, we investigate the chances of survival of a new kind of information traders named believers which have been introduced in the previous chapter, who interact with traditional rational traders. These new type of traders are affected by cognitive illusions and misinterpret the relevance of their information in predicting future asset values. Using an evolutionary game theoretical set up, we show that the magnitude of the illusions affects traders' behavior and survival. Moreover when illusions are powerful, believers trade aggressively ensuring their survival in the long run.

7.1 Introduction

Based upon evidence from studies in psychology and decision making, several authors have investigated departures from full rationality in both economics and finance. Within the latter field, the common goal among these works is the attempt to explain anomalies in securities markets (see Barberis and Thaler (2002) for a complete survey). Financial research has focused on several aspects of investor's psychology resulting in incorrect expectations about asset payoffs. A great attention has been devoted so far to the role played by overconfidence in driving investors' misperception about returns. When predicting future prices, overconfident people set too narrow confidence bands and as a result get surprised more often than they anticipated. As a consequence, overconfident traders underestimate risk and trade more aggressively, as shown by De Long et al. (1991) and more recently by Hirshleifer and Luo (2001).

In the previous chapter we have shown how the presence of believers influence prices and returns. In this chapter we focus in the survival of believers by relying on the evidence that people often perceive relationships that in fact do not exist. Such behavior is known in the psychological literature as illusory correlation. Taken together, these two chapters demonstrate the impact of illusions in financial markets and the likelihood that such a biases are persistent.

Perhaps the London bombing during World War II constitutes the clearest illustration of the illusory correlation bias (see Gilovich (1991) and the references therein). During the latter stages of the World World II, when Germans bombarded London with their "vengeance weapons": the V-1 buzz bomb and the V-2 Rocket, Londoners asserted that the weapons appeared to land in definite clusters, making some areas of the city more dangerous than others. However an analysis carried out after the war, by R. Clarke (1946) indicated that the points of impact of these weapons were randomly dispersed throughout London.

Figure 1 shows the points of impact of the V-1 and V-2 bombs in central London.

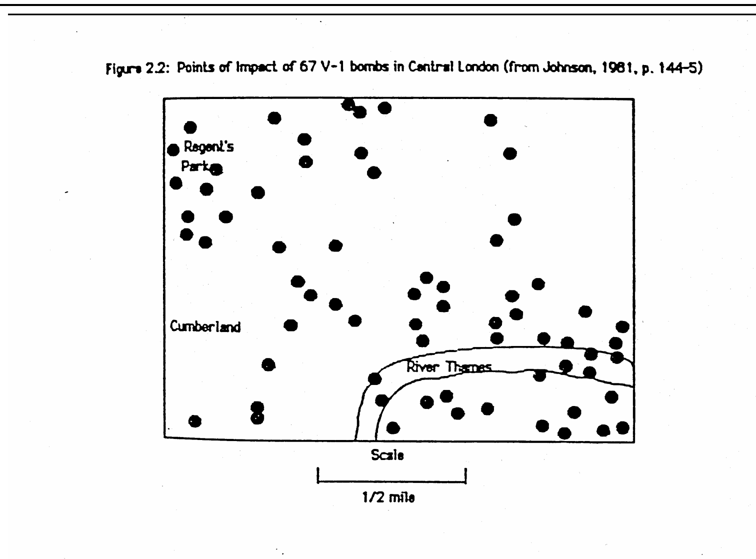


Figure 7.1: The impact of V-1 bombs in London during WWII (source: Gilovich)

Even though the points of impact appear to be random, Londoners asserted that some areas of the city were more dangerous than others because weapons hit the ground in clusters.

The lower right quadrant looks devastated and the upper left quadrant also looks hard hit. The upper right and lower left appear to be relatively tranquil. After a first look at the picture we can easily understand how the presence of special target areas could have seemed to Londoners to be an irresistible product of their own experience both vertically and horizontally. If we create four quadrants of equal area, as it was discussed before, this results in an abundance of points in the upper left and the lower right, and a dearth of points in the other two areas. However a proper statistical test shows this clustering to be a significant departure from an independent random dispersion.

In other words when the dispersion of points is caved out in this particular way, no-chance clusters can be found. It is the existence of clusters that creates the impression that the bombs did not fall randomly over London. Moreover, if the figure is bisected by two diagonal lines, then no significant clusters would be found.

The above example shows how people experiencing illusory correlation tend to find regularities in events that are truly random.

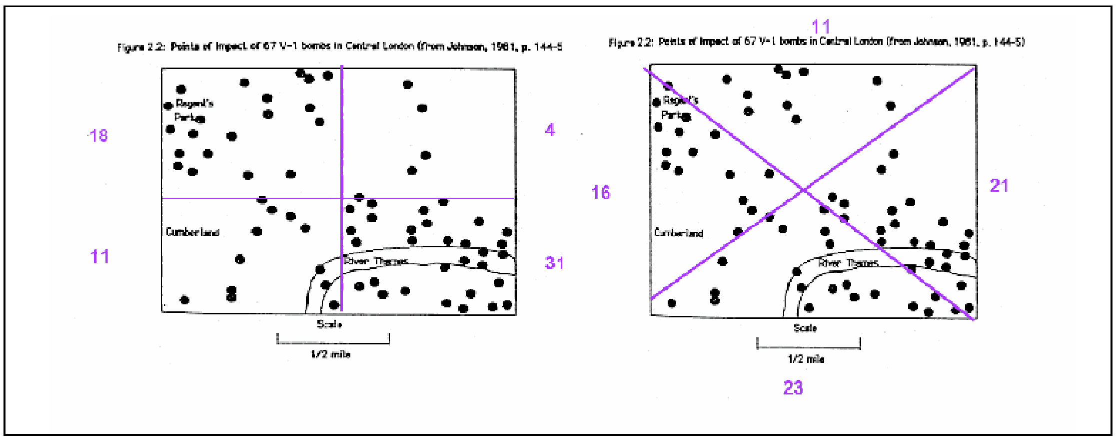


Figure 7.2: Different perceptions on the impact of V-1 bombs in London during WWII (source: Gilovich)

Another important and controversial example about illusory correlation is provided by Aroson (1994) who has shown that many people assume a relative high risk when estimating the risk of HIV in lesbians even though HIV infection rate for lesbians is not only lower than for male homosexuals, but also for the all male and female heterosexuals. The reason for this false estimate appears to be that most of the people carry the following schemata in their head: "Homosexuals are associated with a high risk of HIV" and "Lesbians are homosexuals". Both statements are objectively correct, but the conclusion of perceiving is wrong since it is based in perceiving a relationship that does not exist.

In finance Goldberg and Von Nitzsch (2001) argue that illusions may explain initial public offerings in the high-tech sector. The first high-tech firms to be quoted in the NeuMarkt offered high returns due to their good future prospects. However investors incorrectly anticipated a positive relation between going public *per se* and high growth rate, rather than between the latter and sound future earnings.

Imagine an investor bought 10 different stocks and all the stocks whose company name begin with A go up in price while all the others go down. It is very likely that given his current level of arousal (i.e happiness) and his time constraints, this will cause him to leap to an illusory correlation between the company name and rising stock prices. Consequently, he will start buying more stocks that begin with A. A random distribution of returns in a rising market would suggest, incorrectly, that stocks beginning with A go up more often. Moreover, due to an ever-increasing percentage of stocks in his portfolio beginning with A, he fails to see that stocks that begin with other letters go up in equal percentages.

At this point, the reader may say that is ridiculous. Admittedly, we have made the example extreme to illustrate the idea. But evidence shows that people do it all the time without realizing. Let us take technical analysis as an example. If investors buy several stocks when they rise above their 20 day moving average and they make money on them, they will create an illusory correlation between the two. As long as they can spot the pattern sometimes and make money on it, which reinforces the correlation in their mind, they will continue to look for it and bet on it. It doesn't matter that the pattern often fails to hold true: they will continue to believe in the correlation.

The problem as we have seen in chapters 1 and 2 is that to create the correlation in their minds is very easy. It only requires a tenuous association between an event and a reward. But to disprove the correlation is hard. Few people are going to sit down and calculate the correlation coefficient between price and the 20 day moving average!

Finally, as shown in Huberman (1999) there are many "news" that may attempt to capture our attention even though most of them should be considered more noise than reliable signals: "On sunday May 3, 1998 *The New York Times* carried an article on a potential new drug being researched by EntreMed. EntreMed's stock price rose USD 85 from a close on the previous friday of just over USD 12. The stock subsequently fell back during trading on Monday 4 May to a close respectable USD 52. Three weeks later the stock price was still above USD 30.

Many academics reading this example may say that this is a typical example of markets incorporating new information and this is exactly the point of this story. There wasn't new information. the potential breakthrough had been reported no less than five month in earlier in *Nature* and in numerous popular newspaper including *The New York Times.* So enthusiastic public attention induced a permanent rise in EntreMed's share price, even though no genuine information had been given to the market and the relevant information was objectively reported many month before.

As is clear illusions consist in establishing correlation among events which are unrelated. Consistently, we consider a model in which two classes of informed traders coexist. Rational traders constitute the first group, and correctly assess the relevance of their information in predicting asset returns. Believers experience illusory correlation, and constitute the second type of informed agents. These traders are boundedly rational because they misinterpret the relation between signals and the asset payoff. In analysing such trading enviromnent we closely follow the work by Hirshleifer and Luo (2001), which consider similar interaction between rational and overconfident traders. In particular, we first focus on a static competitive setup and then introduce evolutionary dynamics to study the long-run properties of our static equilibrium.

Our main results relate both the trading activity and survival of believers to the illusion quality, which measure the degree of illusory correlation they experience. When the illusion quality is low, believers overestimate risk and as a consequence they take conservative positions in the risky asset. Such a behavior reduces their trading strategy profitability (with respect to rational traders), and believers do not survive in the long run. On the other hand, believers tend to trade more aggressively than rational agents when experiencing high quality illusions. This way believers are better equipped at exploiting profitable opportunities created by liquidity traders and the long-run equilibrium involves a positive fraction of believers. As is clear, introducing illusory correlation in financial markets proves to be flexible enough to encompass previous behavioral models such as Hirshleifer and Luo (2000) on overconfidence, and Bernard and Thomas (2002) on underconfidence.

The remainder of the chapter is organized as follows. Section 1 defines the illusory correlation bias by reviewing the relevant contributions to the psychological literature. Section 2 characterizes the static competitive equilibrium in a competitive financial market with rational traders and believers. The long-run properties of such a market are investigated in section 3. Finally section 4 concludes.

7.2 Illusory correlation

Illusory correlation is a cognitive illusion (or illusion of thinking) which shows a severe failure and inaccuracy in correlations assessments. This phenomenon was first documented by Chapman (1967) and Chapman and Chapman (1967), in their work on word association and clinical psychologists (see also chapter 15 and 17 in Kahneman et al.(1982)).

In their famous study Chapman and Chapman (1969) wondered why clinical psychologist continued to use certain projective tests in psychological diagnosis, particularly the Draw-a-Person Test, even though these tests had been shown to be useless. In a Draw-a-Person Test, patients are ask simply to draw a human figure on a blank sheet of paper. It was thought that "patients" project various aspects of their personalities into their drawing. For example, suspiciousness of others was thought t be associated with atypical eyes, and concern about manliness were thought to be associated with brought shoulders. Many studies have shown that these ideas were simply wrong. when drawings made by paranoid patients (who are suspicious) were compared with drawings by people who are psychologically normal, no differences are found in the eyes. What really was striking is the fact that clinical psychologists continued to use the test although they knew about the findings. Informally, many of them said that they simply did not believe the negative results. the most striking response for Chapman and Chapman came from a colleague of them who deliberately told them " I know that paranoids don't seem to draw big eyes in the research labs, but they sure do in my office" (Chapman and chapman 1971 pp 18-19)

To find out whether people were really capable of detecting such correlations, they collected a number of these drawings and labeled them with a psychological characteristic, such as "suspicious of other people", "has had problems of sexual impotence". The labels for each picture were carefully chosen to ensure that they was absolutely no correlation, within the set of pictures, between the label and the features of the human figure thought to be associated with it. For example, human figures with elaborated sexual features were as likely to occur when the label did not indicate sexual concern as when it did. These drawings with the labels were shown to college students who had never heard about the Draw-a-Person Test. When they were asked to discover what features of the drawings tended to go with the what labels, students "discovered" exactly the correlation that most clinicians believed to be present - for instance suspiciousness, and abnormal eyes- even thought there was no statistical correlation. Note that subjects were asked to describe what characteristics of the drawings went with what labels of the drawings they were shown, they were not asked what they thought was true in general.

As Chapman himself noticed, illusory correlations are not restricted to the domain of clinical judgments. Most superstitions essentially are empirically groundless beliefs about the associations between particular actions or events and subsequent positive or negative outcomes. Racial, ethnic, regional, religious, or occupational stereotypes similarly are beliefs about covariations, beliefs that are strongly held and remarkably resistant to the impact of non-supporting data.

Chapman and Chapman studies were considered dramatic, controversial, and of considerable immediate relevance to the practitioner. Thus they triggered a large body of studies concerned with the subjective correlation assessments that deviate more or less markedly from the correlation actually encountered.

The ability to figure out the correlations that hold between signals and their meanings, is a basic tool of adaptive intelligence. The psychology literature accounts for three classes of illusory correlations phenomena: (i) expectancy-based illusory correlations which suggest that observers tend to see the regularities that they do expect to find (ii) illusion arising from unequal weighting of information, which generally occurs when present events and committed behavior are deemed more important than absent events or omitted behaviors, and (iii) illusory correlations reflecting selective attention and encoding which happens when some observations catch more attention or are more likely to be encoded in memory and remembered than others. As is clear, all the three classes lead to the subjective overestimation of zero causal, complementary, or reciprocal relationship between two events.

Consistently with the evidence contained in the psychological literature, we consider in the next section traders who misperceive the relevance of the information they possess in predicting future asset values.

7.3 Static model

7.3.1 Asset markets

Two securities are traded in a one-period competitive market: a riskfree asset with gross payoff normalized to 1, and a risky asset with final payoff f, where $f \sim N\left(\bar{f}, \sigma_f^2\right)$.

7.3.2 Agents

Three types of traders are active in the market: rational traders, believers, and noise traders. Rational traders and believers are informed traders, in the sense that they receive some payoff relevant information (specified below, see section 7.3.3) before trading takes place. We normalize the size of informed traders to 1, and let λ and $1-\lambda$ denote respectively the fraction of rational traders and believers. In what follows the relevant variables for rational traders are denoted with subscript r (similarly for believers we use subscript b). Informed traders maximize expected utility over final wealth $\{w_i\}_{i=r,b}$. We assume that trader i's utility is exponential, $U(w_i) = -e^{-\gamma w_i}$, where $\gamma > 0$ denotes the absolute risk aversion coefficient, assumed equal across informed traders. Without loss of generality, informed traders are endowed with zero initial wealth, such that their final wealth is given by the gains from investing in the two assets. Since the risk-free security has a unity payoff, one has $w_i = x_i(f-p)$, where x_i is trader i's demand for the risky asset, and p is its price. Finally noise traders submit random demand $x \sim (0, \sigma_x^2)$ with x orthogonal to f.

7.3.3 Information structure

We denote each trader's information set by Ω_i, for $i = r, b$. Both rational traders and believers receive a polysemous signal s of the final payoff, say $s = f + \varepsilon$, where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ and orthogonal to f.

As it has been explained in Chapter 1, the problem traders face with polysemous signals is that its properties of physical things tend to persist when the context has changed. However the significance of a thought, idea or partial state of mind depends upon which other thoughts are active in time and what eventually emerges from the conflict with other senses. In other words since the signal is polysemous, the implicit and explicit significance are not the same, thus the informational content of the signal is ambiguous. [1]

Rational traders correctly assess the signal's informational content, i.e. $\mathrm{Cov}_r(s,f) = \sigma_f^2$, as well as its precision, i.e. $\sigma_s^2 \equiv \mathrm{V}_r(s) = \sigma_f^2 + \sigma_\varepsilon^2$. On the other hand, believers misinterpret the relevance of s in providing payoff relevant information. More specifically, believers, due to the ambiguity of the signal, are prompt to be affected by the illusory correlation phenomena conjecturing that $s = \alpha f + \eta$, where $\alpha > 0$ and $\eta \sim N(0, \sigma_\eta^2)$ is orthogonal to f. We refer to the parameter α as the illusion quality, since it measures the magnitude of the believers' misperception. In fact, the signal's informational content for a believer is given by $\mathrm{Cov}_b(s,f) = \alpha\sigma_f^2$.

By means of the illusion quality α we aim at capturing the illusory correlation bias (see Section 7.2) in an intuitively and simple way. Recall from the London bombing example that people sometimes see (causal) relationships where there are none, thus incorreclty assessing the relevance of the evidence. When bringing the idea of illusory correlation to financial markets we thus model investors affected by illusory correlation as misinterpreting the relevance of their private information (the signal s) in predicting the asset payoff.

We assume that the signal's precision is correctly assessed by a believer, i.e. $\mathrm{V}_b(s) = \sigma_s^2$, and consequently set $\sigma_\eta^2 = \sigma_s^2 - \alpha^2\sigma_f^2$. For σ_η^2 to be well-defined, i.e. non-negative, we set $\alpha \in (0, \sigma_s/\sigma_f)$. As will be clarified in the section below, the assumptions on the uncertainty structure guarantee that when projecting f on the polysemous signal, the regression coefficient used by a believer differs from the one estimated by a rational trader.

[1] For a more in deep explanation about intentionality and ambiguity when the signal implicit and explicit significance differ, please refer to chapter 1, section 1.3, and Saussure (1967).

In other words, due to the ambiguous nature of the signal, rational traders correctly assess the informational content and relevance of the signal. On the other hand, believers misinterpret the informational content of the signal triggering expectancy-based illusory correlation, assigning to the signal much more relevance that what it should objectively have.

The distribution of the fundamental value, the signal structure (thus including the illusion quality α) and the fraction of rational traders, λ, are common knowledge among market participants. Also, the assumption of symmetry of believers can be relaxed but with no additional insight.

7.3.4 Equilibrium

Under our distributional assumptions on the final payoff and the signal, it follows that trader i's problem is given by:

$$\begin{aligned} &\max\nolimits_{x_i}\ \mathrm{E}\left(w_i|\,\Omega_i\right) - \tfrac{\gamma}{2}\mathrm{V}\left(w_i|\,\Omega_i\right) \\ &\text{s.t. } w_i = x_i\left(f-p\right) \end{aligned} \tag{7.1}$$

From the constraint in (7.1) it emerges that solving trader i's problem entails finding the first two moments of f conditional on the information set $\{\Omega_i\}_{i=r,b}$. Letting $\beta_r = \sigma_f^2/\sigma_s^2$ and making use of the Projection Theorem yields

$$\begin{aligned} &\mathrm{E}\left(f|\,\Omega_r\right) = \bar{f} + \beta_r\left(s-\bar{f}\right) \quad ; \quad \mathrm{E}\left(f|\,\Omega_b\right) = \bar{f} + \alpha\beta_r\left(s-\bar{f}\right) \quad ; \\ &\mathrm{V}\left(f|\,\Omega_r\right) = \beta_r\sigma_\varepsilon^2 \quad \text{and} \quad \mathrm{V}\left(f|\,\Omega_b\right) = \beta_r\left(\sigma_s^2 - \alpha^2\sigma_f^2\right) \end{aligned} \tag{7.2}$$

such that trader i's demand function is given by

$$x_i = \frac{\mathrm{E}\left(f|\,\Omega_i\right) - p}{\gamma\mathrm{V}\left(f|\,\Omega_i\right)} \quad , \quad i = r, b. \tag{7.3}$$

The illusion quality α affects believers' trading behavior as follows. Suppose that $\alpha \in (1, \sigma_s/\sigma_f)$. From the conditional moments in (7.2) one has that $\beta_b = \alpha\beta_r > \beta_r$ and $\mathrm{V}(f|\,\Omega_b) < \mathrm{V}\left(f|\,\Omega_r\right)$, such that eq. (7.3) gives $|x_b| > |x_r|$. When the illusion quality is large, believers overestimate the asset's conditional mean and underestimate its conditional variance. As a result, excessive volume would emerge due to believers taking larger positions than rational traders. On the other hand, if $\alpha \in (0,1)$ then $\beta_b < \beta_r$ and $\mathrm{V}(f|\,\Omega_b) > \mathrm{V}\left(f|\,\Omega_r\right)$. In this case believers trade less aggressively than rational traders, i.e. $|x_b| < |x_r|$. Therefore a relatively low illusion quality is consistent with the trading behaviour of underconfident (or pessimist) traders.

As the analysis of traders' demand schedules reveals, illusory correlation can induce believers to trade more aggressively or more conservatively with respect to rational investors depending on the value taken by the illusion quality α. The former trading behaviour emerges in HL as well, so that our model indeed nests HL whenever α is sufficiently large. The regression coefficient in each trader's assessment of the final payoff conditional on the signal is fundamentally driven by the correlation between f and s. In HL overconfident traders correctly assess the covariance between f and s while underestimate the signal variance. As a result, correlation between final payoff and signal is overestimated and the posterior mean puts more weight on the signal w.r.to the prior. In our model, believers correctly assess the signal precision while fail at pinning down the correct covariance between f and s. In particular, when the illusion quality is large enough ($\alpha > 1$), they overestimate $cov\,(f, s)$. As a result, the regression coefficient in eq. (7.2) is biased upwards. It should be noted that for $\alpha > 1$ our model is observationally equivalent to HL, i.e. an econometrician estimating investors' demand schedules will see excessive volume in a market with overconfident traders as well as in a market with high illusion quality. However, our model is richer than HL in terms of the demand schedules we can generate. Whenever $\alpha < 1$ believers will underestimate the covariance between the asset value and the signal and would take conservative positions. This cannot happen in HL since, by construction, boundedly rational traders cannot underestimate the signal precision. All in all, our model implies that whenever excessive volume is detected in empirical analyses this does not necessarily point at the presence of overconfident traders. First, another bias -high quality illusory correlation- can be responsible of high volume. Second, excessive volume may indeed stem from *rational* traders (not boundendly rational investors) in the presence of a low quality illusory correlation. However, as the survival analysis reveals (see Section 7.4) evidence consistent with the latter explanation is typically a short run phenomenon.

Equipped with traders' demand functions, we now turn to derive the equilibrium price. Market clearing requires that

$$\lambda x_r + (1-\lambda)\, x_b + x = 0 \tag{7.4}$$

Substituting traders' demand (see eq. (7.3)) into the market clearing condition (7.4) gives the equilibrium price

$$p = \bar{f} + \psi^{-1}\varphi\beta_r\left(s-\bar{f}\right) + \psi^{-1}\gamma\beta_r\sigma_\varepsilon^2\left(\sigma_s^2 - \alpha^2\sigma_f^2\right)x \tag{7.5}$$

where φ and ψ are positive scalars given by

$$\varphi = \alpha\sigma_\varepsilon^2 + (1-\alpha)\,\lambda\left(\sigma_s^2 + \alpha\sigma_f^2\right)$$

$$\psi = \sigma_\varepsilon^2 + \left(1-\alpha^2\right)\lambda\sigma_f^2$$

Note from (7.5) that the equilibrium price is an unbiased estimate of the average final value $\bar{f}$, i.e. $E\,(p) = \bar{f}$. Moreover for $\lambda = 1$ the price is equivalent to the fully rational price p^r

$$p^r = \bar{f} + \beta_r\left(s-\bar{f}\right) + \gamma\sigma_\varepsilon^2\beta_r x$$

Equivalently p^r can be obtained setting $\alpha = 1$ in (7.5). In fact, both cases would correspond to all traders behaving rationally.

Trader i's unconditional profits are given by

$$E\left[\pi_i\,(\lambda)\right] = E\,(\pi_i) = \mathrm{E}\,(x_i(f-p))$$

Since the equilibrium price is centered around $\bar{f}$, expected profits coincide with the unconditional covariance between x_i and $(f-p)$.[2] Therefore:

$$E\left[\pi_r\left(\lambda\right)\right]=\frac{\sigma_\varepsilon^2}{\gamma\psi^2}\left[\left(1-\alpha^2\right)\left(1-\lambda\right)^2\sigma_f^2+\gamma^2\beta_r\left(\sigma_s^2-\alpha^2\sigma_f^2\right)^2\sigma_x^2\right] \quad \text{and}$$

$$E\left[\pi_b\left(\lambda\right)\right]=\frac{\sigma_\varepsilon^2}{\gamma\psi^2}\left[-\left(1-\alpha^2\right)\lambda\left(1-\lambda\right)\sigma_f^2+\gamma^2\beta_r\sigma_\varepsilon^2\left(\sigma_s^2-\alpha^2\sigma_f^2\right)\sigma_x^2\right]$$

Using the above equations the difference in expected profits of the two types of traders $\Delta=\Delta(\lambda)$ is

$$\Delta\left(\lambda\right)=E\left[\pi_r\left(\lambda\right)-\pi_b\left(\lambda\right)\right]=\frac{\sigma_f^2\sigma_\varepsilon^2\left(1-\alpha\right)}{\gamma\psi^2}\left[\left(1-\alpha\right)\left(1-\lambda\right)+\gamma^2\left(1+\alpha\right)\beta_r\left(\sigma_s^2-\alpha^2\sigma_f^2\right)\sigma_x^2\right] \tag{7.6}$$

7.4 Model dynamics

We consider an evolutionary process for traders allowing types to replicate over time based on the profitability of their strategies i.e. new generations are born each time and they become rational or believers depending on the relative success of past players. This criterion is quite standard in evolutionary game theory and stems from the observation that traders use the strategies which turned out to be profitable in the past, thus imitating successful strategies. Examples of individual behavior based on adaptation and imitation of successful strategies can be found in standard evolutionary game theory textbooks such as Taylor and Jonker (1978), Weibull (1995), Fundemberg and Levine (1998), and Luo (1999) among many others.

Suppose at time t the expected profit for a rational trader (resp. believer) is higher than the one for a believer (resp. rational trader); then at $t+1$ the proportion of rational traders increases (resp. decreases). If at time t both strategies yield the same expected profits, then the proportion of traders remain unchanged at $t+1$. The fraction of rational traders follows the dynamics

$$\lambda_{t+1}=\lambda_t+f\left(\Delta(\lambda_t);\lambda_t\right) \tag{7.7}$$

where the expected profit differential $\Delta\left(\lambda_t\right)$ is defined in (7.6). The function $f(\cdot):\mathbb{R}\times[0,1]\rightarrow[0,1]$ is assumed to be continuous and to satisfy the following properties (see Hirshleifer and Luo (2001)):

i) $f(\cdot)=0$ if $\Delta(\lambda_t)=0$ and $\lambda_t\in(0,1)$

ii) $f(\cdot)<0$ if $\Delta(\lambda_t)<0$ and $\lambda_t>0$

iii) $f(\cdot)>0$ if $\Delta(\lambda_t)>0$ and $\lambda_t<1$

iv) $f(\cdot)=0$ if $\lim_{\lambda_t\rightarrow0^+}\Delta(\lambda_t)\leq0$

[2] Computing profits therefore boils down to taking covariances between the random variables f, s and x. As is clear, these covariances are the 'correct' ones, i.e. the ones a rational trader would correctly postulate.

v) $f(\cdot) = 0$ if $\lim_{\lambda_t \to 1^-} \Delta(\lambda_t) \geq 0$

The equation for the fraction of rational traders in (7.7) together with the above properties essentially specifies a replicator dynamic model (see for example Fundenberg and Levine (1998)). An alternative way to introduce dynamics in our model would be to keep the population fractions fixed and make the illusion quality α change over time. One could specify a dynamic equation for α similar to the one in (7.7) and embed it with properties equivalent to $i) - v)$ above. This alternative dynamics would be consistent with the idea that strategy profitability affect the bias, rather than population fraction. However there is an abundant literature documenting that 'individuals are slow to change their beliefs in the face of new evidence' (see Shiller 2000) and are prone to ignore 'any information that conflicts with their point of view' (see Montier 2002). Both conservatism and confirmatory bias thus naturally lead our choice to dynamically model λ rather than α.

It is important to stress that our dynamic model considers a competitive financial market which by definition means that there are no strategic aspects (i.e. dull criticism). New generations are born each time and they become rational or believers depending on the relative success of past players.

Conditions $i), ii)$ and $iii)$ describe the replicator's behavior when $\lambda_t \in (0, 1)$, while the behavior at the extrema 0 (all believers) and 1 (all rational traders) is characterized by conditions $iv)$ and $v)$. We are interested in determining the existence and uniqueness of an equilibrium value for the fraction of informed traders, which we denote by λ^*. As is clear, this boils down to identify conditions under which the replicator equation (7.7) admits an interior fixed point viz. a corner solution.

We let the economy be represented by a vector of parameter values $\mathcal{E} = \left(\alpha, \gamma, \sigma_f^2, \sigma_\varepsilon^2, \sigma_x^2\right)$, and focus our attention on admissible economies[3] as the ones characterized by:

$$\mathcal{E} \in ((0, \sigma_s/\sigma_f) \setminus \{1\}) \times \mathbb{R}_+^4.$$

Like the following Proposition reveals, the illusion quality plays a crucial role in determining the equilibrium fraction of traders.

Proposition 1. For all admissible economies there exists a unique dynamic equilibrium given by:

A. $\lambda^* \in (0, 1)$ if and only if $\alpha \in (\hat{\alpha}, \sigma_s/\sigma_f)$

B. $\lambda^* = 0$ if and only if $\alpha \in (1, \hat{\alpha})$

C. $\lambda^* = 1$ if and only if $\alpha \in (0, 1)$

where $\hat{\alpha} \in (1, \sigma_s/\sigma_f)$ solves $\alpha^3 \kappa \beta_r + \alpha^2 \beta_r \kappa + \alpha (1 - \kappa) - (1 + \kappa) = 0$ and $\kappa = \gamma^2 \sigma_f^2 \sigma_x^2$.

[3]We exclude $\alpha = 1$ as an admissible parameter value because in this case one cannot distinguish rational traders from believers.

According to Proposition 1, the survival of traders depends on the believers' misperception, as captured by α. Rational traders and believers coexist whenever the illusion quality is sufficiently high. The rationale behind the first finding is analogous to the one proposed by Hirshleifer and Luo (2001). In fact, high values of α imply that believers underestimate risk thus taking larger positions than rational traders. Thus believers better exploit the misvaluation that noise traders create in the market. Once the fraction of believers is large enough though, prices would move against them and rational traders would gain by trading in the opposite direction. As a result, both types of traders survive in the long run. Whenever the misperception is not very large (Proposition 1-part B), believers still take more risky position than rational traders. However in this case believers engage in somewhat milder risk-taking trades. As a result prices do not move against them enough for rational traders to profitably take the opposite positions. Therefore believers are the only ones surviving in the long run. Finally, whenever believers underestimate the signal relevance in providing payoff-relevant information, i.e. $\alpha \in (0, 1)$, then they are driven out of the market (Proposition 1-part C). Low values for α imply that believers overestimate risk, and as a result their trades are conservative. This way they are not able to exploit the misvaluation created by noise traders and thus do not achieve the returns enjoyed by rational traders. As a consequence they disappear in the long run.

Analysing how the fraction of believers surviving in the long run is affected by the underlying parameters is relevant. We have:

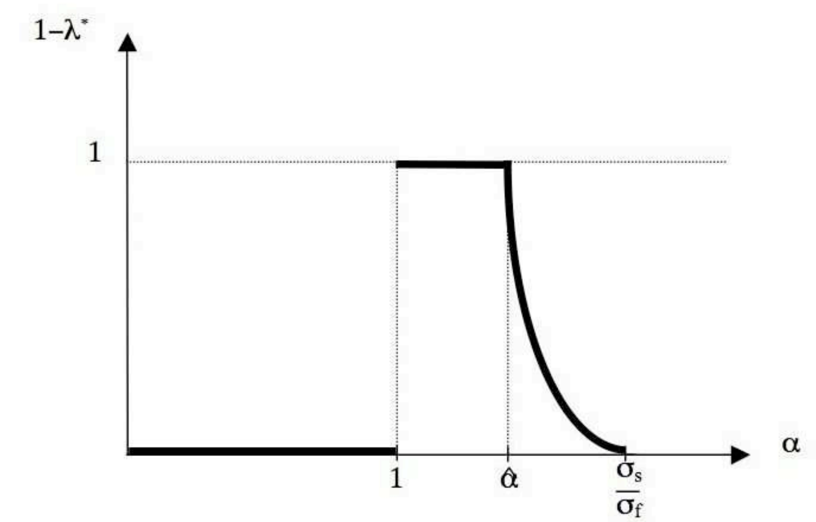


Figure 7.3: Survival of Believers

Corollary 1: Let $\alpha \in (\hat{\alpha}, \sigma_s/\sigma_f)$ such that $\lambda^* \in (0, 1)$ by Proposition 1-part A; then the lower is the proportion of believers that survive in equilibrium

A. the lower is noise trading volatility (σ_x^2)

B. the higher is the illusion quality (α).

As shown in figure 7.3, the comparative statics results stem from believers' risk underestimation whenever the illusion quality is sufficiently high, i.e. $\alpha \in (\hat{\alpha}, \sigma_s/\sigma_f)$. The source of believers' profits comes from the misvaluation generated by noise traders. Believers are better equipped (with respect to rational traders) to profit from these opportunities because their trading is more aggressive. As a consequence, the fraction of believers is positively related to such profit opportunities as measured by the liquidity trading variance, σ_x^2. Similarly, we know that the illusion quality positively affects trading aggressiveness. When the illusion quality is very high, believers trade too aggressively and the fraction surviving in equilibrium decreases.

7.5 Conclusion

We propose a model where rational traders coexist with believers affected by illusory correlation. Such a psychological bias results in believers misinterpreting the relevance of their information in predicting future asset values. We show that the magnitude of illusory correlation affects traders' behavior and their ability to survive in the long run. When the illusion quality is low, believers trade too conservatively and do not survive in the long run. On the other hand, high illusion quality implies aggressive trading and enables a fraction of believers to survive in equilibrium.

The model predicts that a high illusion quality results in excessive volume (see section 7.3) and it is a persistent bias (see section 7.4). On the other hand, a low illusion quality generates conservatism and cannot last in the long run. Taken together, these findings imply that excessive volume can persist over long time horizons if and only if the illusion quality is relatively high and that conservatism is just a short run phenomenon. As such, volume analysis might allow us to infer the illusion quality.

Appendix

Proof (Proposition 1): An interior equilibrium value for the fraction of believers is defined by properties $i - iii$ of the $f(\cdot)$ function in the replicator (7.7). By property i the following must hold:

$$\lambda : \quad \Delta(\lambda_t = \lambda) = 0$$

Using (7.6) one has

$$\lambda = 1 + \frac{(1+\alpha)\,\gamma^2 \beta_r \sigma_x^2 \left(\sigma_s^2 - \alpha^2 \sigma_f^2\right)}{1-\alpha} \tag{7.8}$$

As is clear, the numerator of the second term on the RHS in (7.8) is positive. Therefore $\lambda < 1$ if and only if $\alpha \in (1, \sigma_s/\sigma_f)$. For λ to be positive, the following condition must hold

$$g(\alpha; \beta_r, \kappa) = \alpha^3 \kappa \beta_r + \alpha^2 \beta_r \kappa + \alpha(1-\kappa) - (1+\kappa) > 0$$

where $\kappa = \gamma^2 \sigma_f^2 \sigma_x^2 > 0$. Notice that: 1) the terms in α^3 and α^2 are positive, 2) the constant is negative while 3) the sign of the linear term depends on $1-\kappa$. However, regardless of whether $\kappa > 1$ or $\kappa < 1$ there is always a single sign change in the coefficients of the polynomial $g(\alpha; \beta_r, \kappa)$. It follows by Descartes' rule that there is a unique positive root $\hat{\alpha}$ which solves $g(\hat{\alpha}; \beta_r, \kappa) = 0$. Moreover consider

$$\begin{aligned} g(\alpha = 1; \beta_r, \kappa) &= -2\sigma_\varepsilon^2 \\ g(\alpha = \sigma_s/\sigma_f; \beta_r, \kappa) &= \frac{\sigma_s}{\kappa \beta_r}(\sigma_s - \sigma_f) \end{aligned}$$

Therefore $g(\alpha = 1; \beta_r, \kappa) < 0 = g(\hat{\alpha}; \beta_r, \kappa) < g(\alpha = \sigma_s/\sigma_f; \beta_r, \kappa)$, yielding $\hat{\alpha} \in (1, \sigma_s/\sigma_f)$ and $\lambda \in (0,1)$ if and only if $\alpha \in (\hat{\alpha}, \sigma_s/\sigma_f)$. Finally it is straightforward to check that $\Delta(\lambda_t) > 0$ if and only if $\lambda_t < \lambda$ and $\Delta(\lambda_t) < 0$ if and only if $\lambda_t > \lambda$ (properties ii and iii). It follows that λ in (7.8) is indeed an interior fixed point for the dynamics defined in the main text.

We now consider corner solutions for the population dynamics (properties iv and v). The behavior of $\Delta(\cdot)$ at the boundaries is described by the following:

$$\lim_{\lambda_t \to 0^+} \Delta(\lambda_t) = \frac{\sigma_f^2 \sigma_\varepsilon^2}{\gamma \psi^2}\left[(1-\alpha)^2 + \gamma^2\left(1-\alpha^2\right)\beta_r\left(\sigma_s^2 - \alpha^2\sigma_f^2\right)\sigma_x^2\right] \tag{7.9a}$$

$$\lim_{\lambda_t \to 1^-} \Delta(\lambda_t) = \frac{\left(1-\alpha^2\right)\gamma \beta_r \sigma_f^2 \sigma_\varepsilon^2 \left(\sigma_s^2 - \alpha^2 \sigma_f^2\right)\sigma_x^2}{\psi^2} \tag{7.9b}$$

From (7.9a) it follows that if $\alpha \in (0,1)$ then $\lim_{\lambda_t \to 0^+} \Delta(\lambda_t) > 0$. Suppose then $\alpha > 1$. The condition $\lim_{\lambda_t \to 0^+} \Delta(\lambda_t) \leq 0$ is equivalent to $g(\alpha; \beta_r, \kappa) \leq 0$. Therefore $\lambda^* = 0$ if and only if $\alpha \in (1, \hat{\alpha})$. Finally $\lim_{\lambda_t \to 1^-} \Delta(\lambda_t) \geq 0$ if and only if $\alpha \in (0,1)$. ■

Proof (Corollary 1). At the interior fixed point λ^* :

$$\frac{\partial \lambda^*}{\partial \sigma_x^2} = \frac{(1+\alpha)\,\gamma^2 \beta_r \left(\sigma_s^2 - \alpha^2 \sigma_f^2\right)}{1-\alpha}$$

which is clearly negative, since $\alpha > \hat{\alpha} > 1$ at the interior fixed point. Taking the derivative of λ^* with respect to α gives

$$\frac{\partial \lambda^*}{\partial \alpha} = \frac{2\gamma^2 \beta_r \sigma_x^2}{(1-\alpha)^2} h(\alpha)$$

where $h(\alpha) = \sigma_f^2 (1+\alpha)(1-\alpha)^2 + \sigma_\varepsilon^2 > 0$, thus yielding $\frac{\partial \lambda^*}{\partial \alpha} > 0$. ∎

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