

## The Emotional Factor of Expectations in Decision-Making in A Financial Market

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### **Abstract**

**Purpose:** Within an economy, investors base their choices on the future trajectory. Consequently, any economy can be characterized as a responsive system of anticipation. These choices then influence realized returns, setting new trajectories. For a long time, economists operated under the mistaken belief that investors make financial decisions rationally. The primary objective of this review paper is to propose a theory that can explain the emotional factor in financial decision-making.

**Design/Methodology/Approach:** The research relies on universally accepted scientific qualitative and numerical methods, incorporating theoretical approaches.

**Findings:** The paper illustrates how the subjective thinking and hopes of investors in a financial market can explain pricing. By categorizing investors into rational, emotional, and noise traders, it is possible to theoretically model the pricing mechanism. Strategies can also be developed for each category of investor. In conclusion, the model demonstrates the mathematical considerations underlying price determination based on demands, considering that these prices are established by the market maker.

**Originality/Value:** The paper explores the role of investor beliefs in shaping financial market pricing, particularly focusing on different investor categories. A novel participant, the emotional investor, is introduced, characterized by an exclusive reliance on intuition, thereby exerting a substantial impact on market prices. Consequently, adapting to the characteristics of this new market participant is imperative for the implementation of an effective rational strategy. The theoretical concepts presented in the paper offer valuable insights that could streamline and enhance the understanding of this evolving marketplace.

**Keywords:** Decision-Making Process, Emotions, Expectations, Financial Markets, Financial Modeling, Pricing, Rational Investor

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## 1. Introduction

There is a theoretical assumption in the financial literature that every event in the financial market can be easily explained with the help of competent and easy-to-understand models. The flip side of the reality is that the events, occasions, and incidents in the financial markets are more difficult to understand than what they were assumed in advance. Further, investors are active participants in these events and incidents, so it is difficult to understand what is going on within their complex brains. To the best of our knowledge, till today, financial experts are not able to understand how investors behave in the market and what are the consequences of their financial decisions. However, some authors such as Baker & Wurgler (2006) and Rohilla & Tripathi (2022c) tried to decode the outcomes of investors' complex decision-making in the financial market. Financial and economic models assume that investors behave rationally in the financial markets. But the past shows that their decisions are irrational in a place that is multifaceted, active, indeterminate, and full of abandoned information. Many examples from the history of humanity show that human decisions are not as rational as assumed in economic models and this is especially the case in complex, dynamic, uncertain, or dense information environments, for example, financial markets (Hartford Funds, 2020). Based on the above it can be conjectured that the assumption of financial models, such as the rationality of investors, to gauge possible risk and return, quick decision making, the strong form of market efficiency, and to earn riskless return, is untrue. However, Tversky & Kahneman (1974) concluded that decisions are made under uncertainty and tried to answer how biases and heuristics occur and can these biases and heuristics be used to understand economic behavior. We posit that a nuanced examination of the aforementioned dimensions of human behavior holds the potential to enhance our comprehension of financial markets. By delving into these aspects, we aim to provide a more profound and insightful understanding of the intricate dynamics that govern financial landscapes.

A lot of research has been done in the field of behavioral finance because it is of great interest. Some popular works in the aforesaid field were by Reinhart and Brennan (2004), Brozynski et al. (2003), and Menkhoff and Schmidt (2005). Unfortunately, these were mainly oriented toward the behavioral aspects of the funds' performance and failed to analyze the techniques used and the decision-making process adopted by the investors. To the best of our knowledge, till today there is no major research that concentrates on analyzing the complex decision-making process followed by the investors in the financial markets.

The present work aims to explain the pivot role the emotional factor plays in the financial decision-making process and thus contribute to the existing literature on behavioral finance and economics. The participants in the financial market use technology, data analytics, and various instructional strategies and thus form their expectations regarding the possible outcomes. Thus, such a process must be analyzed, but we are interested in only one aspect of this process which is the emotional factor. Among all the species, the human race is the best because it has the power to think and understand. Market participants are human, so they follow a process for financial decision-making. Further, their decision-making process is affected by many factors such as environment, the pressure of uncertainty, timing of the events, and mental state. In our work, first of all, we describe the emotional factor from the perspective of psychology. Further, we aim to categorize market participants (investors) in different categories *viz.* irrational investors (also called noise traders), rational investors, and emotional investors. Using a mathematical model, we try to explain the role of emotional factors in how different investors in the market use different methods to evaluate the information to make a decision. Consequently, fluctuations in asset prices within financial markets emanate from factors extending beyond informational signals; they are intricately intertwined with the emotional responses of investors to past occurrences or anticipated future events.

## **2. A brief expository overview of emotions and decision-making (Review of literature)**

In the realm of behavioral finance, the emotional states exhibited by investors are commonly denoted as investor sentiment. These emotions collectively shape the behavioral patterns of investors, exerting a tangible influence on the dynamics of the financial market (Rohilla, 2023 p. 26). Traditional economic theories often assume that individuals act as rational agents, making decisions based on careful consideration of costs and benefits. This perspective largely overlooks the role of emotions in shaping economic behavior. Behavioral economics, a field that integrates insights from psychology into economic analysis, has gained prominence in addressing these limitations. Psychological findings can shed light on various aspects of economic behavior, such as how individuals perceive risk, make choices under uncertainty, and respond to incentives. Emotions play a crucial role in shaping preferences, risk attitudes, and the evaluation of outcomes. Understanding these emotional factors can lead to more accurate predictions and explanations of economic phenomena. In Kahneman & Tversky (1979) introduced prospect theory, challenging the traditional assumption of purely rational decision-making. The theory incorporates loss aversion, asserting that

individuals are more responsive to losses than gains, with their decisions influenced by emotions. So, emotions may be delineated as the human response to specific circumstances or as the physiological preparation of the human body for a predetermined mode of response (Oatley *et al.*, 2006).

Damasio (1994) categorizes emotions into three categories *viz.* primary emotions, secondary emotions, and background feelings. Primary emotions are particular responses to particular situations *e.g.* anxiety, distress, pleasure, rage, *etc.* In the human experience, innate emotions are subsequently accompanied by concomitant affective states and demonstrate predictability and modularity.

Secondary emotions such as anxiety, excitement, ecstasy, *etc.* are acquired by humans during their experiences while the brain systematically combines the primary emotions with the stimuli faced by them. Psychological evidence posits that secondary emotions receive support from the collaborative functioning of the limbic system and the prefrontal cortex within the brain.

Between distinct emotional states of a human being, there are background feelings that are characterized by a lower intensity. Over a longer period, these feelings aggravated what is referred to as attitude.

It is crucial to recognize that emotions transcend simple mental processes; instead, they represent intricate and diverse arrays of responses, encompassing a comprehensive spectrum of psychological and physical alteration procedures (Slovic, 1969, 1972).

In research for an extended duration, the significance of emotions has been overlooked in the methodology of financial decision-making. But Tversky and Kahneman (1974) asserted that decisions are inherently made within conditions of uncertainty and sought to elucidate the mechanisms behind biases and heuristics. Their investigation aimed to ascertain whether these biases and heuristics could provide insights into the comprehension of economic behavior. Subsequently, Kahneman and Tversky (1979) and Tversky and Kahneman (1974, 1981) formulated the “Prospect Theory”, which serves as a framework for understanding the statistical average behavior of individuals and groups amid conditions of risk and uncertainty. It is noteworthy that conventional theories such as the random walk and efficient market hypothesis are not distinct individual theories but rather endeavors to characterize average behavioral patterns. However, it is noteworthy to acknowledge that psychologists and neuroscientists were among the pioneers in recognizing that emotions consistently exert influence on the decision-making abilities of individuals. Contemporary research in this field indicates that emotions can yield both positive and negative repercussions on

the decision-making process (see Lerner *et al.*, 2015; George & Dane, 2016; Bucurean, 2018; and Sofi *et al.*, 2023).

Emotions without purpose can yield negative results, whereas purposeful emotions can lead to positive outcomes (Frijda *et al.*, 2000). It can be asserted that emotions serve as valuable tools for survival. According to Elster (1998), emotions reduce decision-making delays and enhance the effectiveness of the decision-making process. Lo (2004) introduces the adaptive market hypothesis, which combines behavior based on self-interest and willingness to learn, with market efficiency in financial markets. It is based on the principle that to survive in financial markets, investors make mistakes, learn from them, and subsequently behave adaptively. Their behavior is subsequently mirrored in the market, where they aim to maximize the value of their assets. As elucidated earlier, this value maximization relies on their accumulated experiences and positive expectations regarding anticipated outcomes.

### 3. Investors categories

In the preceding section of the paper, we elucidated the pivotal role that emotions assume in the decision-making processes of participants within the financial market. In the ensuing pages, our objective is to elucidate the tangible manifestations of this emotional factor in actual scenarios within the financial market. We endeavor to empirically demonstrate how emotions influence and shape decision-making dynamics in the real-world context of financial transactions and investments. To conceptualize the phenomenon of emotion within the realm of financial markets, it is imperative to undertake a systematic categorization of investors engaged in the trading of identical high-risk assets.

Participants (also investors) in the financial market are neither fully rational nor fully irrational (also called noise traders) (Slovic *et al.*, 2002; Verma *et al.*, 2008, Kuzmina, 2010; Mukherjee & De, 2019). So, there must be one more category of participants which we can call emotional participants. So, there are three categories of investors *viz.* rational, irrational, and emotional. Further for our work we assume that any decision of an investor is based on how he/she perceives the available information in the market. Now we explain the three categories of investors—

1. **Rational:** Rational investors are those investors who consider the past as well as present information to make any decision regarding the sale/purchase of a financial asset. They use the Bayesian concept to assign equal importance to the past and present information. Also, they do not deny the presence of other types of investors.

2. **Irrational:** Irrational investors are noise traders who make decisions based on their personal beliefs. They follow herd behavior and try to get better returns when the market rises, and they are kicked out of the market when there is a downfall (Rohilla, 2023).
3. **Emotional:** In the realm of financial markets, these investors exhibit indifference to the presence of other participants, and they assign different degrees of probabilities to different information. Based on this assertion, it may be inferred that this category operates either impulsively or conventionally, guided by their personality traits. This behavioral pattern serves as a noteworthy illustration of the recurrent contemplation inherent in their decision-making processes. Emotional investors primarily rely on their instincts and make decisions based on their unique beliefs about prices. Therefore, one can interpret emotional strategy as an illustration of heuristic actions.

#### **4. Mathematical model as the practical implication of the theoretical considerations**

In order to develop any mathematical model certain assumptions are necessary. We have the following assumptions—

1. Time is discrete.
2. There is only one risky asset the price of which is  $\Pi$ .
3. All the participants execute the trade (T) of the asset at the same time.
4. There are no transaction costs.
5. The market facilitator is not biased.
6. The market facilitator is autonomous and no external pressures are there.
7. Insider trading is disallowed.
8. There are only three homogenous groups of investors (participants or traders or players) in the financial market *viz.* rational (superscripted by RA), irrational (superscripted by IR), and emotional traders (superscripted by EM).

The focal point of the current discourse is to delve into the processes by which investors discern relevant information, conduct thorough evaluations, and subsequently integrate these findings into their overarching investment strategies. This examination underscores the pivotal role that information acquisition and analysis play in shaping the decision-making frameworks of investors within the financial landscape. By elucidating the nuanced steps involved in information selection, assessment, and strategic amalgamation, this discussion seeks to contribute to a comprehensive

understanding of the intricate dynamics governing investor behavior and decision processes within academic discourse.

The author's focus will primarily center on rational and emotional investors, with less emphasis on noise investors, given their propensity to act randomly.  $f$  is a probability density function contingent upon a set of public information ( $F_{t-1}$ ) and delineates how each cohort of investors interprets the distribution of current returns. Further, the articulation of beliefs regarding the historical, present, and future developments in the financial market by each rational and emotional investor can be linked to this probability density function ( $f$ ). This analytical framework endeavors to illuminate the intricate interplay between investor psychology, information assimilation, and market dynamics within the context of rational and emotional decision-making processes. Thus, the price of any risky asset for a rational investor in a financial market can be defined as follows—

$$\Pi_t^{RA} = \Pi_{t-1} \cdot E(R_t^{RA}) \dots \dots \dots (i)$$

Where,

$\Pi$  = Price of any risky asset for a rational investor

$\Pi_{t-1}$  = Price of any risky asset at time  $t - 1$

$E(R_t^{RA})$  = Expected log-return on any risky asset for a rational investor

Further, the price of any risky asset for an emotional investor in a financial market can be defined as follows—

$$\Pi = \Pi_{t-1} \cdot E(R_t^{EM}) \dots \dots \dots (ii)$$

Where,

$\Pi$  = Price of any risky asset for a rational investor

$\Pi_{t-1}$  = Price of any risky asset at time  $t - 1$

$E(R_t^{EM})$  = Expected log-return on of any risky asset for a rational investor

This is a fact that every investor in the market processes past and present information in a different way resulting in differences in their beliefs. Such differences are the main reasons for the discrepancies in pricing of the risky assets. Our next objective is to integrate the influence of past and present information-based beliefs into the model. This enhancement aims to capture the nuanced

interaction between investor opinions, shaped by historical and contemporary information, and their impact on the financial dynamics.

Diverse investors exhibit varying evaluations of past information, and their priori perspectives on current returns differ accordingly. Rational investors give regard to the presence and acts of other investors in the market, but irrational investors do not. Irrational investors demonstrate impulsive behavior in the market, relying on their intuition as a guiding factor. The set  $\mathfrak{R}^i$  encompasses the a priori perspectives held by a specific group of investors denoted as  $i$ . This set of perspectives plays a crucial role in influencing the evolution of current prices within the financial market. The symbol  $\Phi^i$  represents an estimation of the joint probability density function characterizing the pertinent a priori opinions within the specific information set of the group—

$$\mathfrak{R}_t^i \subset \{R_t^{RA,Past} R_t^{EM,Past} R_t^{IR,Past}\} \dots \dots \dots (iii)$$

The term “current beliefs of the investors” encapsulates the viewpoints held by specific groups, such as rational or emotional investors, about the potential evolution of present prices based on their respective  $\mathfrak{R}_t^i$ . The given function describes how  $i$  gives importance to priori perspectives in  $\mathfrak{R}_t^i$  and how they affect the current logarithmic returns—

$$\log^i(R; \mathfrak{R}_t^i) \dots \dots \dots (iv)$$

Upon amalgamating the current beliefs of investors across a set of a priori perspectives, subjective probability densities are derived, providing a descriptive account of the specific beliefs held within this amalgamation. The introduced measure represents the probability density function characterizing the priori formulated beliefs specific to the group of investors denoted as  $i$ —

$$f^i(R) = \int_{\mathfrak{R}^{k_i}} \vartheta^i(y) \log^i(R; y) dy \dots \dots \dots (v)$$

Where,

$k_i$  =Number of priori perspectives important for  $i$

$y$  =Important priory perspective

As per the model, rational investor follows a Bayesian decision-making process. Emotional investors exhibit tendencies to either over-react or under-react within the financial market, relying on instinctual decision-making. Moreover, they attribute varying weights (*i.e.*  $a$  and  $b$  ( $b > 0$ )) to their



individual beliefs, contributing to the dynamic nature of their investment decisions. Now, we modify the equation (v) as follows—

$$f^i(R) = K_{a,b}^i \int_{\mathfrak{R}^{k_i}} (\vartheta^i(y))^a (\log^i(R; y))^b dy \dots \dots \dots (vi)$$

Where,

$a$  =weight assigned to past information

$b$  =weight assigned to present information

Whereas the variable  $k$  serves the purpose of ensuring that the function retains its status as a probability density function, thereby adhering to the requisite properties of such a mathematical construct.

$$K_{a,b}^i = \left( \int_{\mathfrak{R}^{k_i} \rightarrow \mathfrak{R}} (\vartheta^i(y))^a (\log^i(R; y))^b dydr \right)^{-1} \dots \dots \dots (vii)$$

Given that rational investors adeptly balance both past and present information, the parameters are assigned equal values, denoted as  $a = b = 1$ . In contrast, for emotional investors, if a greater weight is assigned to past information, the condition  $a > b$  holds true, whereas if a greater weight is assigned to present information, then  $b > a$ . This distinction in parameter values reflects the differential weighting strategies employed by emotional investors in considering past and present information. The distinct beliefs held by various groups of investors imply the existence of multiple subjective probability distributions representing their respective sets of beliefs. This diversity in subjective probability distributions underscores the varied perspectives and expectations present among different investor groups. To streamline our mathematical model, we opt for the normal probability distribution, a choice made to simplify the representation of probability density functions and facilitate the analytical framework.

Once the investors have made judgments about the pricing of the risky asset, they must decide funds to be committed to the trade of such an asset. We know that the prices proportional to the current total order flow are fixed by the risk-neutral stock exchange  $Qua_t$ —

$$\Pi_t = \Pi_{t-1} + \lambda Qua_t \dots \dots \dots (viii)$$

Where,  $\lambda > 0$  and  $\frac{1}{\lambda}$  measures the market depth. So,  $\lambda$  must measure the market depth in a reversed measure. Further,  $Qua_t$  equals all buy and sell orders placed by all the three homogenous groups of investors and can be expressed as follows (where,  $N$  is the total number of investors in each group)—

$$Qua_t = N^{RA}Qua_t^{RA} + N^{EM}Qua_t^{EM} + N^{IR}Qua_t^{IR} \dots \dots \dots (ix)$$

In light of the foregoing deliberations, a model can be formulated to address inquiries about how investors discern the strategy (buy or sell) and ascertain the quantity of assets of an order. As previously elucidated, rational investors adhere to conventional principles to maximize their wealth, grounding their decisions predominantly in reasoned analysis. In stark contrast, emotional traders delineate their strategies through intuition, and their decision-making processes are significantly influenced by affect, in contrast to the random actions of noise traders. This dichotomy in decision-making approaches underscores the multifaceted nature of investor behaviors within the financial landscape.

Rational investors always want to maximize their wealth but at the same time, they have an urge to neutralize the risk. We assume that the selling price of any risky asset ( $V$ ) cannot be zero, so  $V \geq 0$ .

The anticipated wealth, denoted as  $Ov$ , for the rational investor is an outcome derived from sequences of executed trades. The formulation of the demand strategy for this specific investor group, contingent upon a positive  $\lambda$  condition, is expressed as follows—

$$\begin{aligned} Max(Ov) = Ov_{t-1}^{RA} + & \left( \frac{V}{2\frac{1}{\lambda}N^{RA}} - \frac{N^{EM}Qua_t^{EM} + N^{IR}Qua_t^{IR}}{2N^{RA}} \right) \\ & \times \left( V \right. \\ & \left. - \frac{1}{\lambda} \left( N^{RA} \left( \frac{V}{2\frac{1}{\lambda}N^{RA}} - \frac{N^{EM}Qua_t^{EM} + N^{IR}Qua_t^{IR}}{2N^{RA}} \right) + N^{EM}Qua_t^{EM} + N^{IR}Qua_t^{IR} \right) \right) \dots \dots \dots (x) \end{aligned}$$

Rational investors, try to maximize  $Ov$  use the available information, and their decision-making process is based on the ideas and actions of emotional and irrational investors. This reflective and information-driven approach is characteristic of rational investors as they navigate the complexities of the financial market. Building upon this premise, the demand strategy of a rational investor can be articulated as—

$$Qua_t^{RA} = \beta + \beta^{RA}(R_t^{RA} - 1)P_{t-1} \dots \dots \dots (xi)$$

Irrational investors base their decision-making process on personal judgments and beliefs so their demand strategy can be articulated as—

$$Qua_t^{IR} = \beta + \beta^{IR}(R_t^{IR} - 1)P_{t-1} \dots \dots \dots (xii)$$

So,  $Qua_t$  can be represented as follows—

$$Qua_t = \frac{V}{2\frac{1}{\lambda}} + \frac{N^{EM}Qua_t^{EM} + N^{IR}Qua_t^{IR}}{2} \dots \dots \dots (xiii)$$

Thus, equilibrium return on risky asset derived as a summation of subjective returns, as expressed as follows—

$$r_t \approx \frac{V}{2\Pi_{t-1}} + \frac{1}{2}(N^{EM}\beta^{EM}r_t^{EM} + N^{IR}r_t^{IR}) \dots \dots \dots (xiv)$$

The symbol  $\beta^{EM}$  signifies the degree of responsiveness in the demand concerning price expectations.

We assume that the role of emotional and noise investors in the price-setting mechanism is substantial. Their impact is directly proportional to their presence in the market but constrained by available liquidity. The inclusion of emotional investors allows analysis of emotion's impact on decision-making, with a notable association between higher emotional presence and increased market returns and volatility. Similarly, elevated emotional demand sensitivities *i.e.*  $\beta^{EM}$  contribute to heightened market dynamics. Additionally, utilizing unbalanced information in investment strategy formulation correlates with lower market volatility.

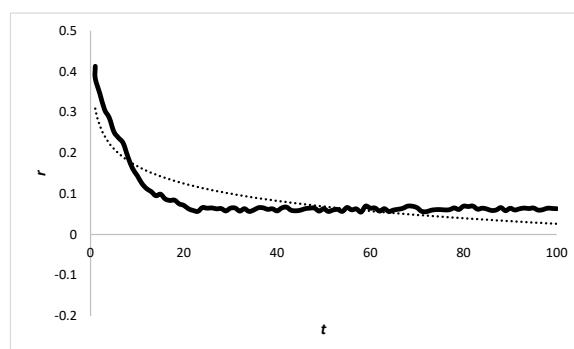
The subsequent section will employ simulation techniques to analyze the evolution of market returns, as well as the rational and emotional wealth derived from the theoretical framework established in the mathematical model. It is important to highlight that the results presented below are provisional findings and may differ under alternative assumptions. To maintain clarity, only the most significant results will be outlined. The following conclusions are based on average values obtained from  $n = 10$  rounds, each comprising  $T = 100$  trade times. The testing population comprises  $n=100$  traders, with a fixed number of five noise traders and variable numbers of rational and emotional traders (Microsoft Excel® was used for the compilation of data obtained from simulation techniques and the preparation of charts). Following Hasbrouck's (2007) methodology, the inverse market liquidity is

set at 0.08. The scenario assumes a low proportion of emotional traders, constituting 25 percent of the financial market. The initial step involves generating normally distributed noise terms with the specified standard deviations. Utilizing these parameters enables the derivation of emotional subjective returns in both logarithmic and gross forms. Following the computation of the present subjective returns, the demand from each group of traders, coupled with their respective wealth, is ascertained. Drawing from the theoretical model and data simulations, the ensuing conclusions are noteworthy—

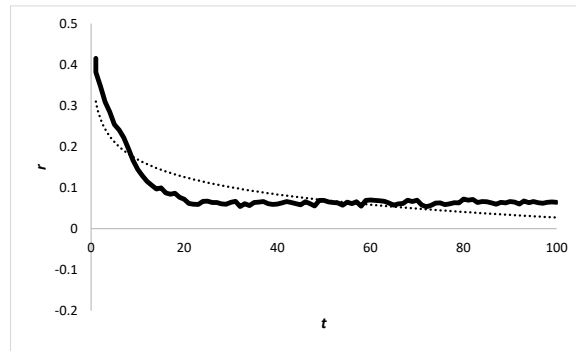
- a. consistent with observations in the theoretical segment, market volatility is expected to decrease;
- b. when there is a more pronounced asymmetry in the emotional combination of past and current belief elements.

This is exemplified in Figures 1-3, where log-returns are more volatile for lower  $b=a$  ratios, signifying a conservative belief formation among emotional traders.

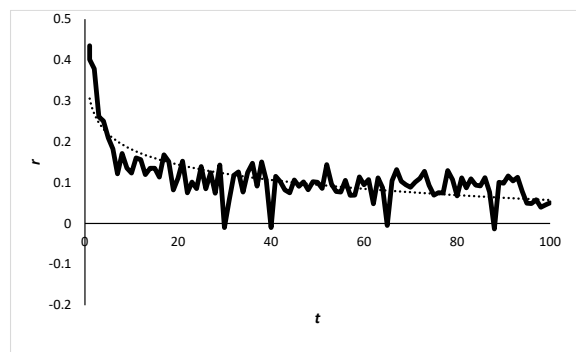
In a general sense, markets affected by emotionally guided activities, as adapted by rational traders, demonstrate resilience to non-recurring shocks but concurrently display inefficiencies, leading to a certain degree of predictability in prices. If emotional investors have a conservative belief, then there is a reduction in the stability of price movements and it leads to predictability. Figures 4-6 illustrate the demands of each trader group, with emotional demand averaging positive, indicating a preference for buying the risky asset. For a lower  $b = a - ratios$  demand is highly unstable and follows a more pronounced upward trajectory. It is worth noting here that the activities of emotional or noise trading individuals are higher in comparison to rational traders in all cases. While the rational group faces an increased total order flow from other traders, its numerical strength ensures individual participation at lower levels (Figures 4-6).



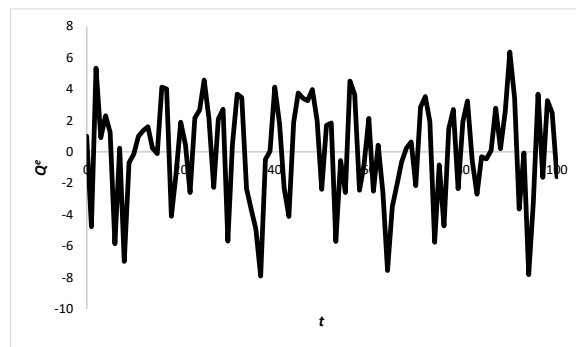
**Figure 1:** Log>Returns with Belief Weight Ratio=100 (Emotional Traders)



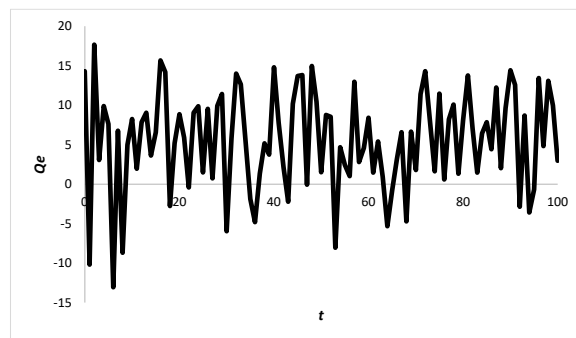
**Figure 2:** Log-Returns with Belief Weight Ratio=1 (Emotional Traders)

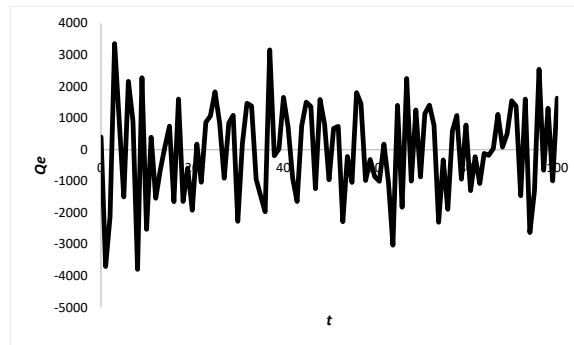


**Figure 3:** Log-Returns with Belief Weight Ratio=0.001 (Emotional Traders)



**Figure 4:** Demand with Belief Weight Ratio=100 (Emotional Traders)



**Figure 5:** Demand with Belief Weight Ratio=1 (Emotional Traders)**Figure 6:** Demand with Belief Weight Ratio=0.001 (Emotional Traders)

## 5. Concluding remarks

The present work gives a mathematical model after examining the role of emotional factor in financial decision-making using simulation techniques. Simulation results demonstrate that different types of investor categories choose the most appropriate plan of selection based on individual opinion formed after examining information with different approaches. Various investor categories adopt distinct approaches, as outlined below—

**Rational Traders/Investors:** Past and current information is used in conjunction with the Bayesian probability model by rational investors to make the most of profits.

**Emotional Traders/Investors:** Emotional investors assign varying weights to information, forming beliefs based on their perceptions. Further, they use commonly available analytical methods and are not affected by the presence of other types of investors/traders *viz.* rational and noise. These investors steadfastly adhere to their beliefs, utilizing heuristics—rule-of-thumb strategies—in decision-making.

**Noise Traders/Investors:** Noise investors are impulsive and their trades are based on irrationality (random trading).

The mathematical model demonstrates that emotional investors can generate profits with their trades in financial markets. When tested in the actual stock market, the results predicted by the model remained the same. Further, there is possibility that these investors may maximize personal wealth in the short run. Over the long term, their survival expectations align with those of rational investors.

In conclusion, the mathematical model reveals that emotional investors, by leveraging distinct decision-making approaches, can achieve short-term financial gains in dynamic markets. However, their long-term survival expectations parallel those of rational investors, emphasizing the intricate interplay between emotions and rationality in shaping financial outcomes.

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