Analysis On Stocks Trading Pattern Based on Framing Effect and Selective Information

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***Abstract*—This paper introduces an analysis of how the trading pattern in stocks can change based on the information provided to the trader. The provided information can be useful or might prove to be a piece of extra irrelevant information. The paper will also go into depth about how the framing effect can result in different trading behavior. The experiment will involve the analysis of both the positive and negative framing effects. The paper will also talk about the disposition effect and how it can affect the judgment of traders. A custom user-friendly GUI was implemented to collect data that doesn't require a sophisticated experimental set-up for performing experiments on multiple people.**

Keywords– Framing effect, Disposition effect, Anchoring effect, Stocks trading

I. Introduction

Traders in the stock market rely on multiple and vast information which can be acquired from various sources. It is well known in the trading firms, "You'll make more because you know more." The information can influence the decision the trader makes while purchasing the stocks. But, it is not necessary that the more information a person has, the more knowledge also is there. There are several irrelevant information in the media, which can cause an ' illusion of knowledge '. This irrelevant information is the main reason which causes the difference in trading behavior. In this paper, it will be discussed how different ways of communication and the quality of information can influence traders in the competitive asset market.

There have been few works in the literature; for instance, [1] shows news media recipients are updated with much news and information, they are prone to the illusion of knowledge. The illusion of knowledge also led to an increase in the number of people participating in the same social media in order to avoid lacking in the race. In [2], the authors analyzed investors, where few investors shifted from phone-based trading to internet-based trading. It was observed in their case that the investors who made the shift to the internet got introduced to a lot of information, and much of them were irrelevant, which also caused less profit as compared to people who decided to stay with the original method. This similar observation was also noted by [3], where online traders underperformed in the market.

In this work, an analysis will be done on more than 40 subjects which will be chosen from a different domains in order to understand different perspectives of people and how they react when several sets of questions will be given to them. The specific contribution of the paper is:

- A competitive stock market trading scenario that will provide an analysis of different trading behavior based on the relevant or irrelevant information provided to the user.
- A robust set of questionnaires to understand people's responses to different negative and positive framed questionnaires.
- Understand how the disposition effect plays a role while trading and how people can fall into its trap. This will be analyzed using the net sum of money the user made.
- Provide an overview of how people with different backgrounds/demographies respond to the situation differently, for people familiar with trading will have some ease in understanding trading patterns compared to a person with a non-trading background.
- Described a new index for measuring how the person would respond to the negatively and positively framed questions based on the past experiences in the sessions, the described index was named as "Happiness Index"

Note the novelty of the work done in this paper as compared to the existing literature [4]. The work in [4] does not provide analysis on the different demographics or education backgrounds as we do. The analysis done on the framing effect was based on semantic variations of a decision problem as done in [5]. While in this work framing was done in a novel way, and participants were told that the dividends will be randomly determined and drawn from a normal distribution. The data was collected with the help of a custom-made GUI that anyone can use and doesn't require any sophisticated experimental setup. Along with this, the method used required less time to collect similar data as in [4]. In the paper [4], participants were called upon to an experimental room, and sometimes in a scenario like this, there are chances that the user responds differently as he/she responds to questions in their natural environment. While in our case, users get involved in the experiment without leaving their natural state, thus providing data as close to real case scenarios as possible. The novelty is also in our questionnaire, where we bring them as close to real trading scenarios as possible. In the paper we also described how the participants will respond to negatively and positively framed questions based on the experiences they had in the past sessions of stock trading, instead of directly measuring the outcomes based on the immediate current session, this was described as the "Happiness Index" in the paper.

The remainder of this paper is organized as follows: details of the framing are provided in Section II. Section III discusses the disposition effect. Section IV describes the dataset and Methodology, and experimental results and evaluations are reported in Section V. Section VI conclude the paper.

II. Framing Effect

It has been noticed in expected utility theory that descriptive invariance should hold for all the cases, according to which it is expected that the different representations of the same choice problem should yield the same preferences. Although this is not always the case, also observed in [6]. For example, in the case of a medical emergency situation, a person has two choices of hospitals; let one hospital say they successfully save 90% of the people, while another advertises itself by saying there is a 10% chance that the person will die. In this case, although both the hospital have statistically the same mortality rate due to different framing, there is a high chance that the person would prefer the first hospital, also analyzed in [6]. In the trade of asset market experiment, participants came across several negatively framed and positively framed questions. In the analysis section, it will be discussed how people responded to those questions. Our experimental approach also involves the anchoring effect, where the participants were provided with some information about the cost of the stock that they might get to buy in the future. This initial segment of information would act as an anchor for the user, and the steps taken by the participants would be in accordance with this anchor. The framing effect in this scenario will help us understand how positive information should increase traders' dividend expectations, while the expectation from negative information is to get lower dividends, this will lead to some particular trading pattern. According to [4] positively framed buyers are expected to purchase assets from negatively rather than from positively framed sellers, while in the case of negatively framed sellers it was expected to sell their assets to positively rather than to negatively framed buyers.

III. Disposition Effect

The analysis also includes the disposition effect, one of the implications of prospect theory. Unlike expected utility theory, the prospect theory-based function defines gain and losses relative to a reference point and not on the basis of the final value. According to the prospect theory, the gain and losses are defined in terms of the concave and convex curves, respectively. If we analyze this statement from the financial point of view, it will then convey that people who experience gain from their investment tend to sell more readily, as compared to the people who experience loss, and they tend to hold on to the money for the longest time, in expectation of getting some gain in the future. An experiment was also performed by [7], where investors held the losing stocks for a median of 124 days, whereas winners only held for 104 days. In this work, we will contribute to the existing literature on the disposition effect by simulating a competitive market scenario and observing the participant's moves, when some will be experienced a loss and some with a gain.

IV. Happiness Index

In order to make the analysis more robust we made a custom analysis index, which will help us to understand the response a user based on the past experiences in the different session. We are calling it as Happiness index. Analysis via this index is similar to how the reinforcement learning work, i.e. in each of the session there will be some sort of gain or loss that the user will experience and based on the past experiences the user will take the decision in the session he is currently in. The happiness index of past experience is denoted by h_{t-1}. The learning rate α is denoting the how fast the user's experience can change. The response of the user based on the change in the happiness index is denoted from by r_t. The final equation to find the current happiness index can be given by:

$$h_t = (1-\alpha).h_{t-1} + \alpha.r_t \tag{1}$$

To understand how the current response of the user can change on the basis of the past experiences, we can split the decision of the users into three parts, buy, hold and sell. Each of these will have different response outcomes. In case of decision to buy the response will be $1 * change$, where the change is defined as the price difference between the current and previous stock price, in multiple of the quantity of the stocks bought. The decision to buy will be based on the pure difference in the prices of the stocks, so the constant 1 is multiplied by the change. While in the case of the hold decision, it can be said that the user could have experienced an equal number of negative and positive gains. While in the case of decision sell, it can be inferred that the person would have been experiencing continuous losses, and so the respective loss response would have a negative constant and magnitude double the decision gain's constant. To summarise the response values, we can look at the below equations:

$$r_t = \begin{cases} 1.change & decision"buy" \\ 0.5.change & decision"hold" \\ -1.5.change & decision"sell" \end{cases} \tag{2}$$

$$change = \frac{(price_t - price_{t-1}) * quantity_t}{100} \tag{3}$$

$price_t$ is the current stock price , $price_{t-1}$ is the previous stock price and $quantity_t$ is the net quantity of stock during transaction The motivation behind using this kind of update rule comes from Reinforcement Learning. A basic reinforcement learning agent AI interacts with its environment in discrete time steps. At each time t, the agent receives the current state s_t and reward r_t. It then chooses an action a_t from the set of available actions, which is subsequently sent to the environment. The environment moves to a new state s_{t+1} and the reward s_{t+1} associated with the transition (s_t,a_t,s_{t+1}) is determined. The reward is high for choosing correct decision and low and even negative for choosing wrong decision. In this case, we treat the subjects as reinforcement learning agents and the game as the environment. The accumulative reward is stored in terms of the happiness index. For transition from one state to another, is associated with ”buy”/”sell”/”hold” decision and ”quantity of stocks”. The coefficients are set such that if the subjects moves in a particular direction and it increases the net worth of the individual, he will be rewarded positively else negatively. A higher penalty is added to the loss producing term and Based on the happiness index we can analyze how the person would respond to the negatively framed and positively framed questions.

V. Demography and Experiment

For the experiment, we tried to collect data with as much variety as possible. There were participants from various range of occupations, such as engineering, commerce, law, management, and others. With a major number of students from the engineering college were the participants. There were a wide range of age groups that participated in the experiment, with the majority lied in the range of 18 to 25 years and maximum age of the participant went up to 54 years.
There were also a distribution between the male and female genders, where the number of male participants counted up to 30 and female participated counted up to 11. To summarize the distribution we can refer the plots given in figure V.

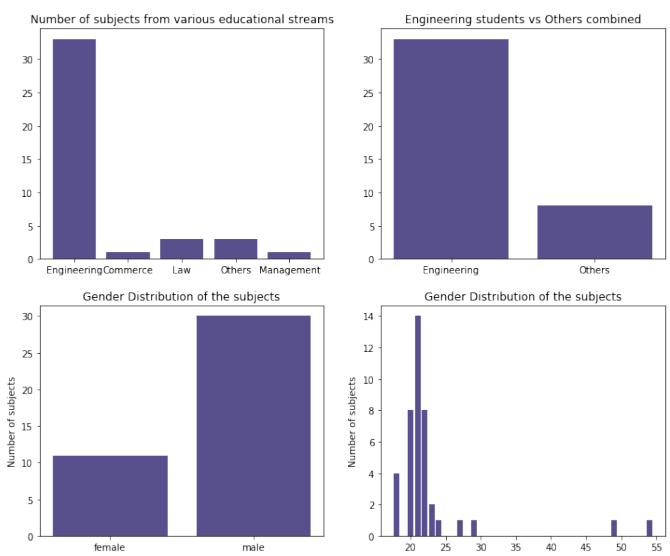


Fig. 1. Demography of the subjects. The top left shows the distribution of subjects based on their educational background. The top right shows the distribution when subjects other than engineering students are combined into one category. The bottom left shows the gender-wise distribution of the subjects. The bottom right shows the distribution of subjects based on their ages.

Statistic	Mean	Median	Min Age	Max Age
Age	22.71	21	18	54

Statistical values defining the age distribution

Gender	Male	Female
Count	30	11

We divided our experiment into two parts, first part we conducted the lottery and second part was stock market simulation. The lottery was conducted in order to measure the attitude of the players toward the risk. The money that the players will be earning via the lottery, will be added to the initial amount of money that the participants will be given when starting the stock market simulation. The lottery would be framed such that the 50% of the participants will be told about the the initial price of the stocks that will encounter at the starting phase of the second part of the experiment. This extra information, given to the participants will act as anchor. There will be two choices given to the participants, in one they will be told that they will be given ’X’ amount of money for sure and in second option they will be told that they will be given ‘Y’ amount of money with 30% chance, and 70% chance to get nothing. The percentages are chosen such that the expected value of both the cases will be same. For experiment the ’X’ amount corresponded to 600 and ’Y’ corresponded to the 2000. The expected value in our case is 600.
In the second part we conducted stock market simulation, in which participants were given 4000 as initial amount of money. The participants can buy any numbers of stocks based on the they have. There will be total of six sessions and in each session, some information about the company will be provided. These information will be negatively for some participants and positively for rest. These information will be followed by questionnaire. As an example consider a sample question in the session: An IPO is about release, and an investor wants to buy a stock whose current price is 200. This scenario can be pitched in two ways,
• There is a 70% chance of success, and the shares are expected to go up by 45% on the first trading day.
• There is only a 30% chance of failure, but if the IPO succeeds, then the stock price may scale up by almost 45%.

In the above case we can both pitchers convey the exact same meaning. But the first statement is framed optimistically, and the second one is framed pessimistically. The first pitch will result in a successful promotion, whereas the second pitch will fail - it will not persuade the investors.
We have designed questions on the similar stand, but in each session the prices will keep on varying over the period, and each question will be differently framed for different set of participants. Thus, based on the money they will have, they can buy more stocks, and thus the final valuation of the money earned by each person will be analysed based on the choices they would made.
The experiment is designed with the help of React for better user experience. The designed web page was hosted online on Heroku. For avoiding noises in the data an authentication feature was implemented which will verify the email IDs

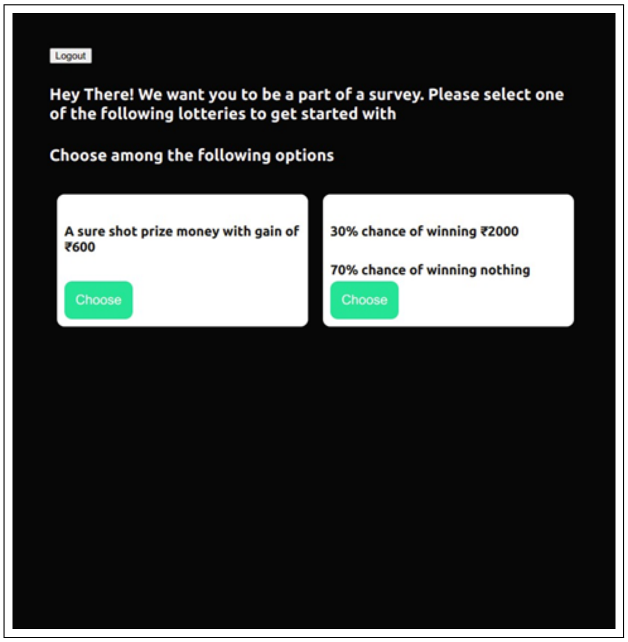


Fig. 2. The interface of the lottery (Part 1 of the experiment).

Fig. 3. The stock market simulation interface (Part 2 of the experiment). The users will be provided with three options, they can either buy, sell or hold on to the stocks. At the end of the experiment, their net worth will be shown.

of the participants and same person cannot give multiple responses. The overview of the designed experiment web-page can be seen in the figure 2, which shows the interface of the lottery experiment, the figure 3 shows the interface of the stock simulation experiment, which is the second part of the experiment and in 5, we can observe the format in which the data will be stored, which would be in JSON format.

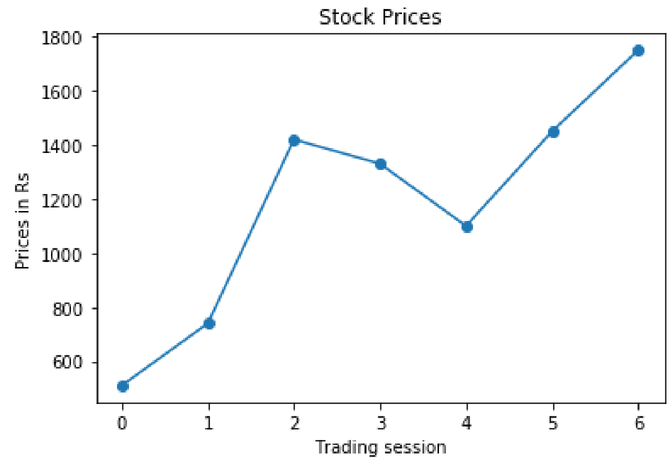


Fig. 4. Stock prices as a function of time/trading session. These prices where hard coded during the trading session because keeping them variable of drawing it from a random distribution would have made the study complex.

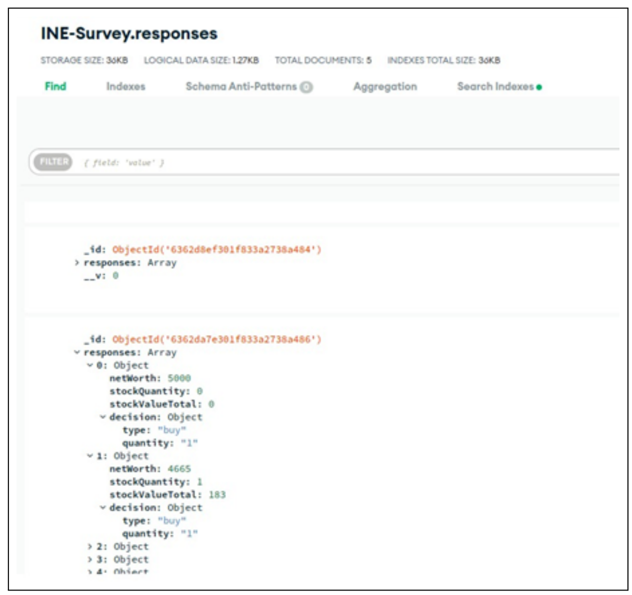
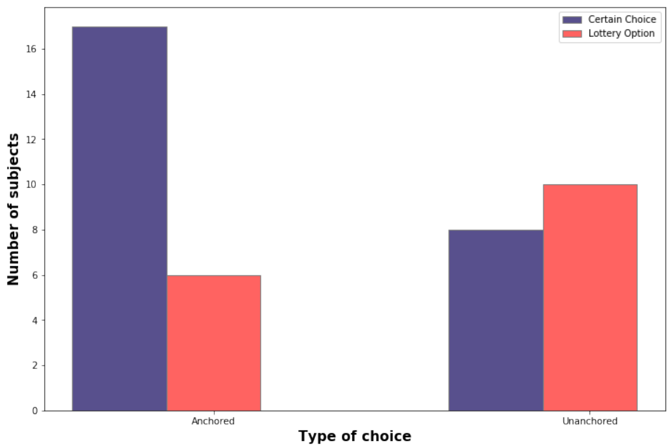


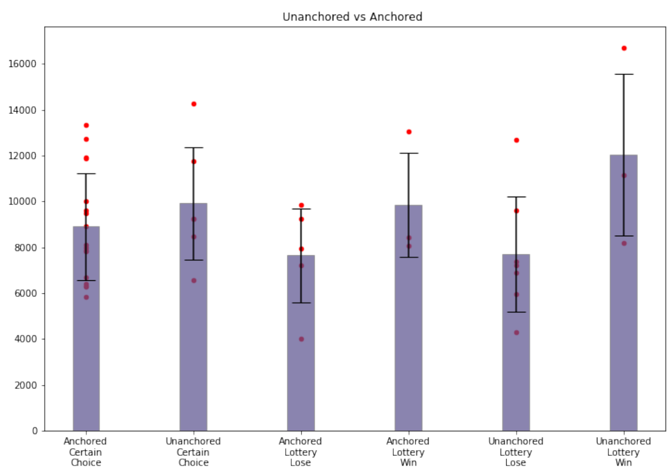
Fig. 5. The data collected from all the participants will be stored in the JSON format.

VI. Results and Discussion

1) Anchoring Effect Results: Fig. 6(a) shows the distribution of the subjects based on whether they were anchored or not. The anchoring information was as follows ”The initial price offer for the stock is 510 and the initial cash given to you is 4000”. This information created an anchor around **510** and **4000** and thus the subjects tended to choose the first choice of certain gain in the lottery. According to our understanding, the certain gain of **600** was much closer to the initial stock price and thus created a bias towards it. On the other hand, people who were not anchored, weren't given any such initial information or anchor and from the results, it is evident that the unanchored people chose the lottery option more often.



(a) Bar plots showing the number of subjects who were anchored with the initial information about the initial stock price and money in their wallet initially. It also shows the distribution of subjects based on the choices they made in the lottery phase.



(b) The final net worth of the subjects based on the anchoring split and their choices in the lottery phase. The blue bar shows the mean of the category and the vertical black line shows the standard deviation. The red points show the actual final state of each subject in the respective category.

Fig. 6. Distribution of the subjects and their final state based on their choices

Percentages For the subjects who were Anchored, 68% of the people opted for the certain choice of 600 and 32% of the people opted for lottery choice. For the subjects who were unanchored , 37.5% of the people opted for the certain choice of 600 and 62.5% of the people opted for lottery choice.

	Anchored	Unanchored
Certain Gain	17	6
Lottery Choice	8	10

Observations Fig. 6(b) shows the final net worth of the subjects after 6 rounds of conditional trading session. The initial choice in the lottery phase has an effect on the final state of the game. The subjects who chose the certain gain choice started with an initial cash of 4600. From the results , it is evident that the subjects who were not anchored by the initial information performed better than the anchored ones. The reason and behaviour for such behaviour is discussed later. The subjects who chose the second choice are divided into 4 categories : (i) Anchored and won the lottery (ii) Anchored and lost the lottery (iii) Unanchored and won the lottery (iv) Unanchored and lost the lottery. It is observed that people who lost the bet ended up performing worse than those who won the bet. The loss in the initial stage put then in an initial state with 600 lesser than those who chose the certain gain option. The subjects who won the lottery started with 1400 more than those who chose the certain choice. Since there is a difference between the starting point , it is not advisable to directly infer results from the final net worth. What we need to is analyse the decisions seperately based on the state of the subject and whether he was positively or negatively framed in that particular trading session. But a loose hypothesis based on the results could be that people who faced loss/no gain (It is considered as a loss because the subjects who lost the bet see it as loss of extra 2000 and according to the prospect theory, it affects them more) in the initial phase performed worse that the others who had either certain gain or who won the lottery. Fig. 7 Shows the temporal

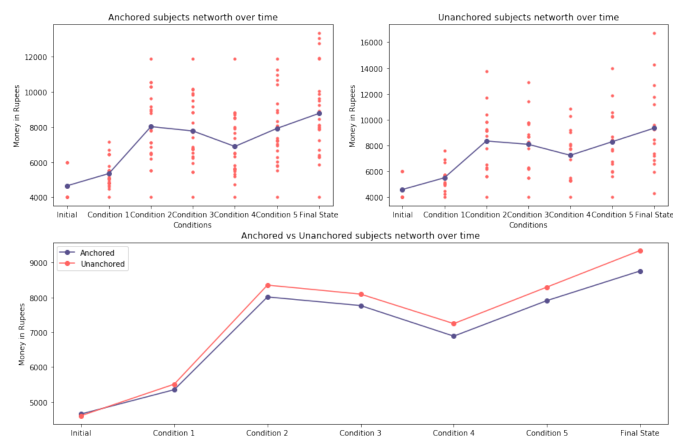


Fig. 7. Top left figures shows the average networth of the anchored people over time. The red points denote the networth of individual subjects. Similarly, the top right figure shows the networth of unanchored people over time and the red points denote the networth of individual subjects. The bottom graph shows the comparision of the average networth of anchored and unanchored people when superimposed over each other.

data representing the networth and average networth across different trading sessions. The issue in drawing inferences from this plot is that this compares the subjects based on the "Anchoring" fact but across different trading sessions, conditions are framed positively and negatively with equal probabilities. The differentiating factor as we move forward in the game is the framing of the conditions and not whether the subject was anchored positively or negatively. The study included the anchoring factor to see the choice of the subjects in the lottery phase. As the game proceeds, all the subjects are shown positively and negatively framed conditions with equal probabilities and hence the anchoring factor becomes irrelevant. We hence form here will differentiate the subjects based the framing conditions.

2) Framing Effect Results: Fig. 8 shows the distribution of number of people being positively or negatively framed over various trading sessions. The framing condition is chosen based on a random variable drawn from a uniform distribution. We can see that for most of the trading sessions, the number of subjects being positively framed is almost equal to the number of subjects negatively framed. Fig. 9(a) shows the histogram of decisions made by the subjects when framed positively on each of the trading sessions. Fig. 9(b) shows the histogram of decisions made by the subjects when framed negatively on each of the trading sessions. It is important to note that the number of positively framed and negatively framed people is varying because of the framing variable which is chosen from a uniform distribution. It also means that it is not necessary for each of the condition to have the same people to be framed positively and same people to be framed negatively always. From the graphs we can infer that initially all the people chose to buy the stock. This might be because they have just entered the game without any perception of the game and they have no initial stocks in their portfolio. The only choice they have is to either buy some stocks initially or to hold. The "Buy" option seems to be more attractive and interactive and thus, most of the people choose this option. Loosely, we can infer few things from the plots:

1) The buy decisions are more in the positively framed category than those in the negatively framed category.
2) In the later stages of the game, negatively framed people bought less number of times than the positively framed people.
3) The participants who were positively framed tend to sell the stocks faster, while in the case of negatively framed case the frequency of sell the stocks was much slower.
4) Hold decision is more common in positively framed subjects
5) There is a peak for selling in condition 3. It was the condition when prices were at all time high and information about data breach was released.
6) The negatively framed participants tend to hold on to their stock more as compared to the positively framed one, and this aligns with the definition of the disposition effect.

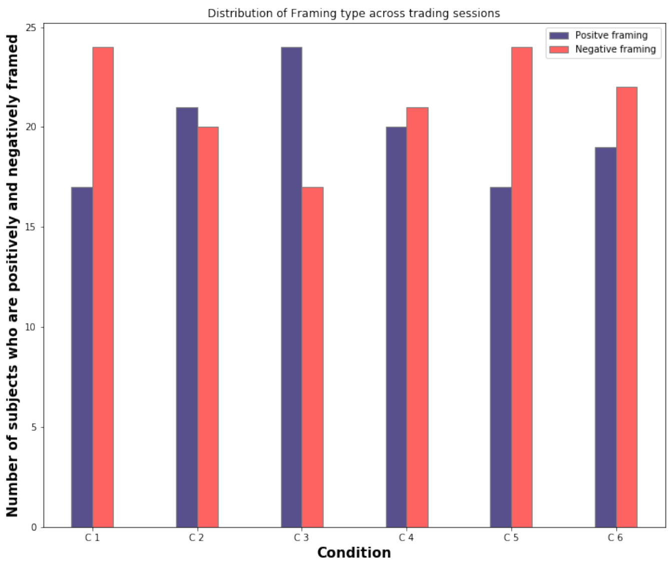
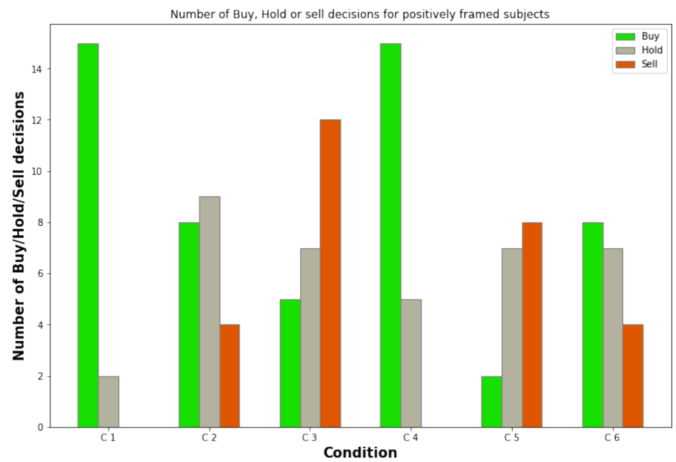
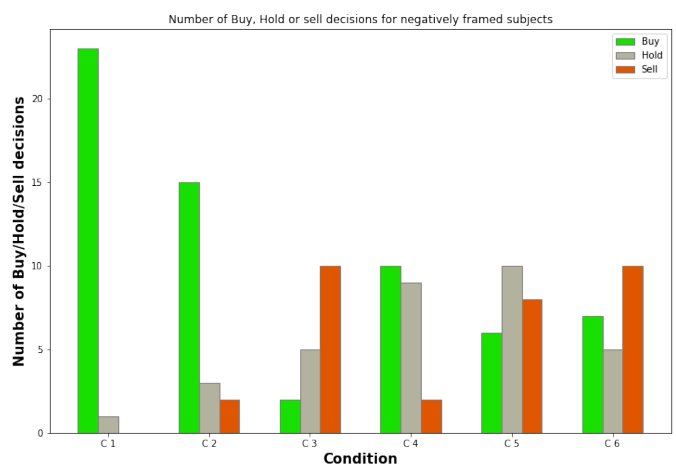


Fig. 8. The bar graph shows the count of number of people positively or negatively framed across various trading sessions.



(a) The plot shows the histogram of subjects choosing "Buy" , "Hold" or "Sell" decision when framed positively.



(b) The plot shows the histogram of subjects choosing "Buy" , "Hold" or "Sell" decision when framed negatively.

Fig. 9. In the above figures, the green colour represents the buy decisions, grey represent the hold decisions and red represents the sell decisions.

Although these inferences are insightful and confirms with the expected outcomes , this method has flaws and loosely drawing conclusions from this plot wont lead to generalized results.

3) Happiness Index: There needs to be a method which normalizes the state of the subjects so that we can compare the effect of positive and negative framing on the subjects. To tackle this issue we came up with a novel idea of "Happiness Index". It tries to quantify the state of the person in terms of happiness. We then try to analyse the effect of framing and loss/gain on the decisions made by the person based on his happiness index. The introduction of this metric tries to generalize the state of subjects irrespective of framing, initial state, anchoring and gain/loss incurred by the person which helps in eliminating the need to categorize subjects based on various states and analysing them individually. Fig. 10 shows the spread of happiness index of the subjects across various trading sessions. Happiness index less than zero indicates that the person is sad and greater than zero indicates that the person is happy. If the index is near to zero, the person is neutral and thus unpredictable.

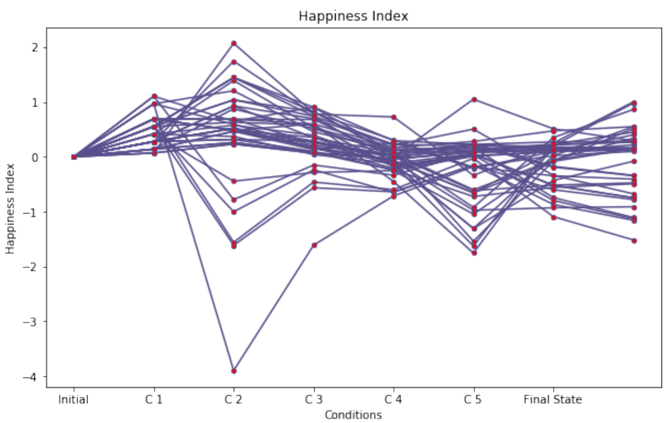
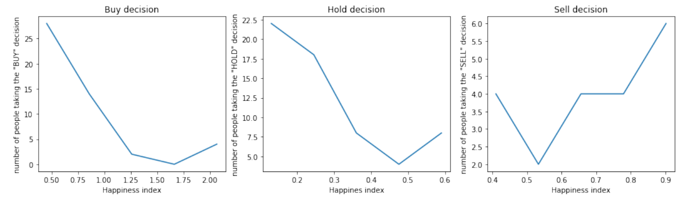
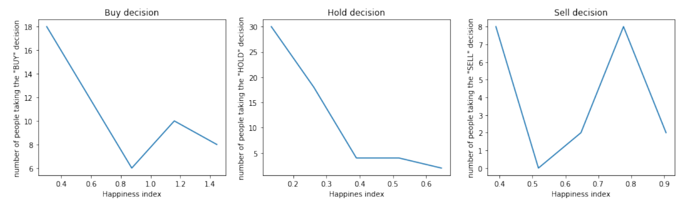


Fig. 10. The plot above shows the happiness index of each of the individuals. The red points shows the absolute happiness index of a subject on C^th condition and a blue curve connecting a set of red points denotes the trace of happiness index of a subject across the experiment. The α for this plot is set to 0.6.

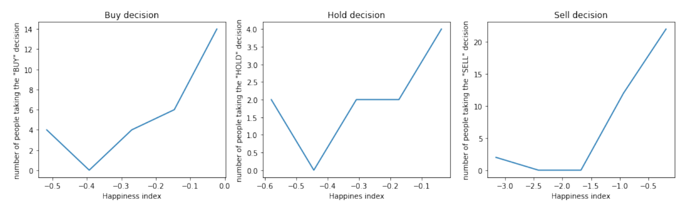
Fig. 11(a), 11(b), 11(c), 11(d) shows the approximate curve based histogram of buy,sell and hold decisions based on the happiness index and type of framing. Fig. 11(a) and 11(b) represent the above mentioned statistics for ”happy” people , i.e. , people with happiness index greater than zero across all the conditions and anchoring groups for negatively and positively framed subjects respectively. We observe that as the happiness index increases, the frequency of buying and holding the stocks decreases but the frequency of selling the stocks increase. The sharp and edgy plots are a result of lower number of subjects, but we expect the curves to be smoother and follow a similar pattern when the test is run on larger number of candidates. From the plots, we can verify the disposition effect : ”Happy people who had a gain initially tend to sell the stocks faster”. Fig. 11(c) and 11(d) represent the above mentioned statistics for ”sad” people , i.e. , people with happiness index lesser than zero across all the conditions and anchoring groups for negatively and positively framed subjects respectively.We can see similar kind of curves in buy and sell decisions and across framing type. We can infer that the people who are sad are risk averse and don’t want to take risky decisions. ”Hold” option is safest when a person is very sad. From the graphs we can see that most of the people choose to hold the data when they are very sad according to the



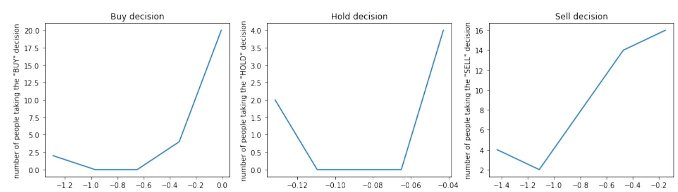
(a) The plot shows the number of buy/sell/hold decisions taken by ”happy” subjects when framed negatively as a function of happiness index.



(b) The plot shows the number of buy/sell/hold decisions taken by ”happy” subjects when framed positively as a function of happiness index.



(c) The plot shows the number of buy/sell/hold decisions taken by ”sad” subjects when framed negatively as a function of happiness index.



(d) The plot shows the number of buy/sell/hold decisions taken by ”sad” subjects when framed positively as a function of happiness index.

Fig. 11. The plots above show the frequency of people taking specific decision based on their happiness state. The plot might seem noisy because of the lower number of participants and distribution of happiness indices.

happiness index. To further see the effect of happiness index on decision making, we monitor the subjects whose happiness changed from either negative value to positive value ,i.e., sad to happy or it changed from a positive value to a negative value , i.e. , happy to sad in Fig. 12. We monitor the number of buy/sell/hold decision just after this transition. We observe that for people who change from sad to happy, sell more because they want to claim more of the rewards and even small amount of happiness wants them to sell the stock. On the other hand, people who change from happy to sad want to get back to their original happiness state and thus buy more in expectation for the prices to go up. The number of hold decision is almost same.

VII. Conclusion

In this work we observed sometimes, extra information can led to change in the trading behaviour. Along with this we

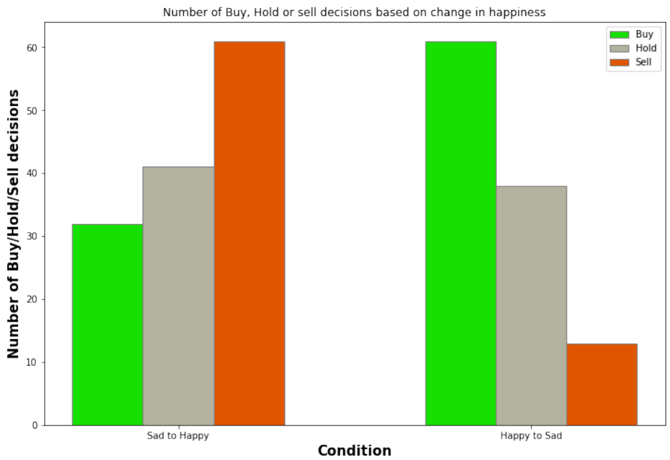


Fig. 12. The decision taken by subjects based on the change in happiness state. If the sign of the happiness index changes, we monitor the behaviour of the subject.

explored two very prominent effects, framing and disposition effects in the trading. An experiment was conducted, which included two parts, in first part we implemented lottery, which was used to analyse risk taking ability of the participants followed by the anchoring effects. For better user experience we designed a React web-app based experiment, which also had the user authentication feature, to reduce the potential noises in the data. The collected data went through several analysis and in order to make the analysis robust, we used a custom measurement index, called the Happiness Index, which is used for measuring the response of a person based on past experiences. The paper showed the negative and positive framing effects on the trading pattern and verified the disposition effect on the participants.

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