Leveraging Cognitive Biases for Investment Optimization: A Deep Learning Approach

Interim Report

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I. Introduction

Human psychology has a major impact on investment decisions in addition to market trends and financial indicators. The importance of cognitive biases in influencing trading behaviors and, consequently, trading results has been highlighted by a number of studies in the subject of behavioral finance. Despite the abundance of research that supports this, traditional approaches to improving trading performance continue to focus primarily on honing pricing tactics. This study tries to refocus attention away from market dynamics and onto the psychological inclinations that control trading decision-making.

The main idea behind this research is to improve trading performance by better comprehending and controlling cognitive biases. In order to uncover and maybe compensate for cognitive biases that affect trading outcomes, we will approach this via the lens of behavioral finance, fusing psychological insights with conventional financial theory.

Data for this study will be gathered using two different methods. First, we will gather historical market data, which will give us the background we need to comprehend the market circumstances that different trading decisions were taken in. In order to assess specific trading behaviors, we will next gather personal trading data. We will be able to make insightful conclusions about how cognitive biases affect trading decisions in various market environments thanks to the comparison of these datasets.

This analysis will heavily rely on feature engineering. We seek to extract behavioral indicators that can act as proxy for various cognitive biases by transforming raw data into meaningful features. The behavioral profiles of each trader will be developed using these bias indicators, revealing the biases to which they are most vulnerable and how these biases affect their trading performance.
The Interactive Brokers API will be used to operationalize this strategy. Real-time tracking and categorization of trading habits will be made easier by this technology. The goal is to categorize trading behaviors in accordance with the cognitive biases they reflect, creating a predictive model that can anticipate when these biases will arise.

We aim to open the door to a more complex understanding of trading behaviors by concentrating on cognitive biases and their impact on investment choices. Not only for individual investors looking to increase their trading success, but also for financial advisers, fund managers, and investment platforms looking to improve their client services and investment offerings, our findings may have important ramifications.

II. Current Progress

A. Determining Cognitive biases

The research has made significant progress. Beginning with the selection of particular cognitive biases that will be investigated in the context of trading activities, our study has looked into these biases in depth. We were able to accomplish this by a careful analysis of the body of research, which enabled us to pinpoint the biases that investors exhibit most frequently and that have the greatest influence. Among these biases are:

Representativeness Bias: The propensity to extrapolate conclusions from a small sample or a single incident. We'll be examining metrics like the frequency of transactions depending on current performance patterns and the use of past short-term performance data in investment selection.

Overconfidence Bias: The propensity to think one is more capable than one is. Trading frequency and the percentage of high-risk investments in the investor's portfolio are two indicators of this inclination.

Anchoring Bias: The propensity to place a great deal of weight on the initial piece of information discovered. When it comes to investments, we'll keep an eye on how long assets are held, particularly those that were purchased at a premium over their current market value, as well as how often the original investment price is brought up.

Fallacy of the Gambler: the idea that historical circumstances have an impact on probability in the future. For this, it will be taken into account how frequently trades are made based on observed patterns or streaks and how many investments are based on believed "luck."

The propensity to give quick or recent information priority is known as availability bias. We'll keep track of how frequently trades are executed right after following newsworthy occurrences and how frequently investors base their judgments on recent news.

Aversion to loss the decision to forego similar rewards in favor of preventing losses. Here, it will be taken into account how long winning stocks are typically held while losing ones are typically sold.

Regret Aversion: The propensity to put off making decisions in order to avoid regretting doing so. We'll examine the avoidance of decision-making during times of turbulence in the market as well as the number of opportunities lost as a result of inaction.

Mental accounting: The propensity to classify money according to individual standards. We'll examine how different accounts handle risk differently as well as how much "windfall" money is invested vs regular income. The bias against being unduly optimistic about anticipated results. Underestimating prospective losses and overestimating potential profits will be signs of this bias.

A solid data extraction framework has also been created. We seek to develop a thorough behavioral profile for each trader by concentrating on data that can serve as trustworthy indications of these biases. This is a crucial stage since the accuracy and usefulness of the data directly affect the reliability of our conclusions. Our current success in locating the necessary data for each prejudice lays a solid platform for the research's subsequent phases.

We will use the Interactive Brokers API as we go along to track and categorize trading actions in real-time. This tool will assist in creating a prediction model that can anticipate when these biases may show up in trading. The current advancements in defining and locating the required data have given us a strong foundation for the remaining stages of this project. By concentrating on cognitive biases, we want to advance our knowledge of trading habits and open the door to better-informed financial choices.

B. Data Type

Our study adopts a two-pronged approach towards data extraction to ensure a comprehensive analysis of the cognitive biases and their impact on investment decisions. We aim to extract historical market data and individual trading data to identify key features indicative of these biases.

The historical market data, comprising price trends, volumes, and other market indicators, will provide a broader context for understanding investment decisions. It allows us to see how investment behaviors correlate with overall market trends and if biases emerge more prominently during specific market conditions.

In contrast, the individual trading data will provide insight into specific investor behaviors. By examining the details of each trade, we can determine the presence and intensity of various cognitive biases. Here's a representation of the biases we aim to investigate and the corresponding data extraction strategy for each:

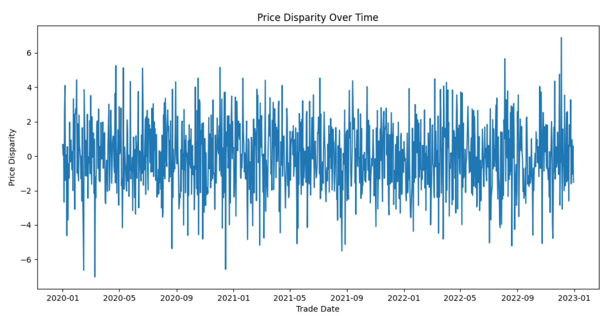
Data Extraction	
Representativeness Bias	Frequency of trades made based on recent performance trends, reliance on short-term performance history for investment decisions
Overconfidence Bias	Trading frequency, proportion of high-risk investments in the portfolio
Anchoring Bias	Holding period of investments, particularly those bought at a higher price than current market value, frequency of reference to initial investment price
Gambler's Fallacy	Frequency of trades made based on perceived patterns or streaks, proportion of investments based on perceived "luck"
Availability Bias	Frequency of trades made immediately after news events, reliance on recent news for investment decisions
Loss Aversion	Average holding period for losing stocks, frequency of selling winning stocks while holding losing ones
Regret Aversion	Avoidance of decision-making during volatile market periods, number of missed opportunities due to inaction
Mental Accounting	Differences in risk-taking between different accounts, proportion of "windfall" money invested vs. regular income
Optimism Bias	Underestimation of potential losses, overestimation of potential gains

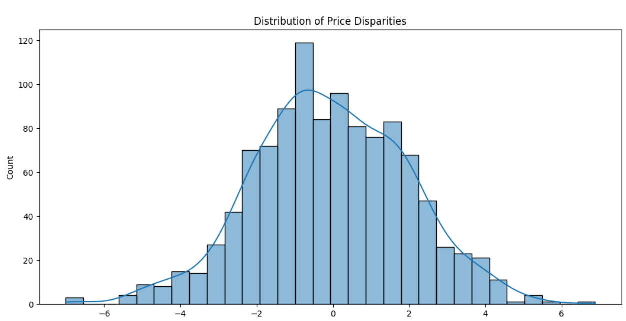
The data extraction process has been initiated with the selection of appropriate tools and methods. We have chosen to utilize the Interactive Brokers API to obtain individual trading data. This powerful tool enables us to track trading behaviors in real-time, providing a rich source of data to analyze and predict the presence of these biases in trading scenarios.

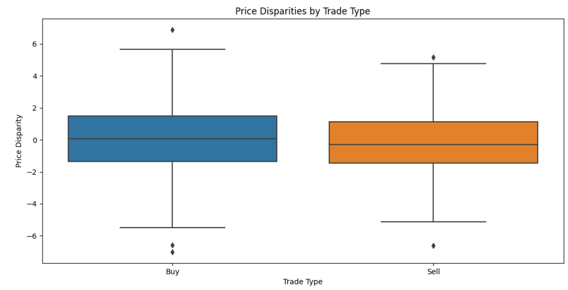
Moving forward, the gathered data will undergo rigorous analysis. The goal is to classify these features and predict their manifestation in real-world trading scenarios, thus offering potential pathways for optimizing cognitive behavior in trading. We believe that such an approach is unique in its focus on behavioral aspects rather than the conventional price-focused strategies, and holds promise for better investment outcomes.

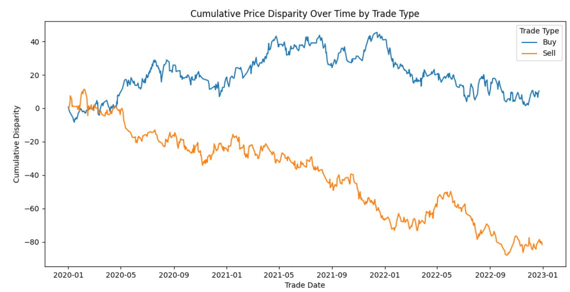
C. Statistical Analysis:

The data was shown on a plot of 'Price Disparity' with time, which gave useful insights. The data demonstrated a substantial pattern of purchasing higher and selling lower than market rates, indicating the presence of overconfidence and loss aversion bias.









Price Disparity Over Time: This line plot depicts the evolution of price discrepancy over time. If the line continually goes upward or downward, it may indicate that traders are routinely overestimating or underestimating the market price. A fluctuating line, on the other hand, indicates that there is no constant bias in one direction.
Price Differences Distribution: The histogram (with a Kernel Density Estimation overlay) depicts the price disparity distribution. If the distribution is biased to the right, it indicates that traders commonly undervalue the market price (since the trade price is frequently lower than the market price). A left-skewed distribution, on the other hand, would imply that traders frequently overestimate the market price.
Pricing Variations by Trade Type: The boxplot shows the distribution of price differences for 'Buy' and 'Sell' trades separately. If the medians differ significantly, it could signal that traders behave differently when buying versus selling. For example, while buying, they may overestimate the market price and underestimate it when selling, or vice versa.
Cumulative Price Disparity by Trade Type: The line plot depicts the cumulative price discrepancy by trade type over time. If the 'Buy' and 'Sell' lines diverge, it may indicate that traders routinely

overestimate the market price when purchasing and underestimate it when selling (or vice versa). This could indicate cognitive biases like overconfidence or loss aversion.

III. Currently In-Progress

Currently, rather than only extracting and analyzing data, we are concentrating on building a predictive model that makes use of both organized and unstructured data. We chose to use Deep Learning (DL) over more conventional machine learning techniques because of the nature and complexity of our task.

Deep learning was chosen because of its innate capacity to handle complicated, high-dimensional data and because it excels at identifying detailed, non-linear relationships within the data. Such a flexible tool is required due to the nature of our task, which is to analyze and forecast cognitive biases in trading behavior. The trading behavior is fundamentally complex since it is influenced by a wide range of variables, such as cognitive biases, market movements, and individual investing preferences. We want to properly capture this complexity within our predictive model by utilizing deep learning.

We must now take a number of crucial actions. We'll do:

- Ensure that the data extraction and cleaning process is complete and that we have dependable, high-quality data for model training.
- Select the deep learning architecture that is best suited to solving our problem, such as a convolutional neural network (CNN) for pattern recognition or a recurrent neural network (RNN) for time series data.
- We should develop and test our model to make sure it is effective and does not overfit or underfit the data.
- Verify the generalizability of our model with previously unreported data.
  Create a system using our model that can give traders timely, practical information.
- Our ultimate objective is to develop a system that can alert users in real time about potential cognitive biases that can be present when trading. These cautions can aid traders in reflecting on their choices and avoiding traps brought on by cognitive biases.

But, we must develop a proper evaluation metric in order to assess the precise impact of these alerts on trading performance. Quantifying the nebulous idea of improved trading performance is difficult. We still need to look at this issue more.

Finally, we plan to implement a backtracking methodology using trading scenarios that include and exclude bias warnings. We intend to measure the difference our technology makes on trading outcomes by contrasting these two scenarios. This in turn can offer convincing proof of the importance of controlling cognitive biases in investment choices.

By following these stages, we want to offer a useful tool that puts cognitive biases at the forefront of the investing decision-making process.