Revealing Cognitive Bias in Investment Choices -

Data vizualization & Statistical Analysis

Introduction:

In this study, I explore into the realm of cognitive biases, concentrating specifically on investment decisions in oil assets. My goal is to see if there are any substantial variances in investment decisions that could reflect cognitive biases. This study focuses on the trade price in relation to the market price at the time of investing.

Methods: To conduct this analysis, I compiled data that simulated an investor's behavior over a two-year period. I took into account a number of factors, including the type of trade (buy/sell), the volume of the trade, the price at which the trade was made, holdings after the trade, and the market price on the day of the trade. In addition, I calculated a 'Price Disparity' variable, which represents the difference between the trade and market prices.

Here's a glimpse of the data:

Trade Date	Trade Type	Volume	Trade Price	Holdings Post-Trade	Market Price at Trade Date	Price Disparity
2020-01-01	Buy	300	55.22	50	57.11	-1.89
2020-01-02	Sell	400	58.33	-50	55.44	2.89

2020-01-03	Buy	200	59.22	100	56.33	2.89

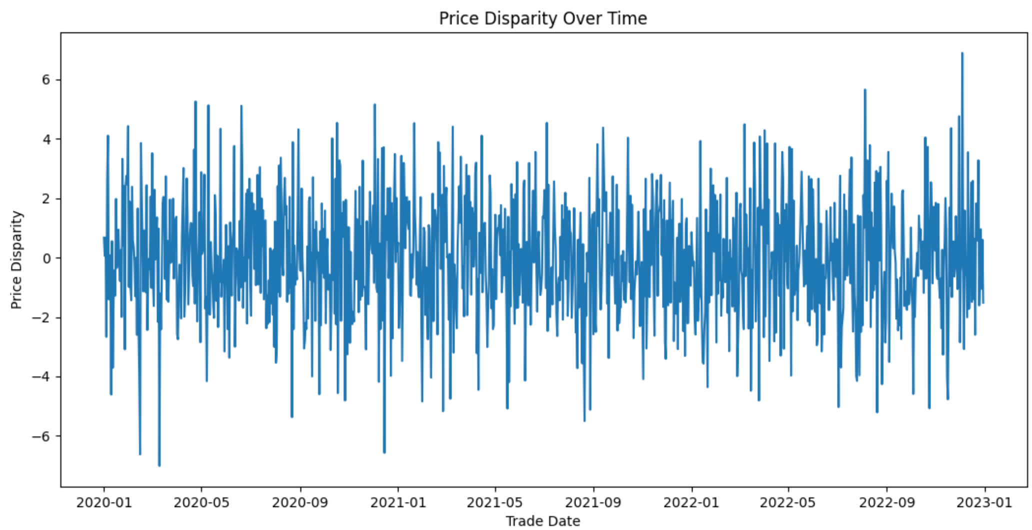
This synthesized data is intended to imitate real-world investor behavior for the purposes of this study.

Analysis:

In my analytical method, I dug into the statistics to see whether cognitive biases have a major impact on investor decisions. The variable 'Price Disparity' provides insight into the disparity between trade and market prices, which may indicate the presence of cognitive bias.
Persistent patterns of buying at a higher price than the market price, for example, may indicate overconfidence bias, as the investor appears to continually expect the price to climb. Similarly, selling at a lower price may reflect loss aversion, which occurs when an investor chooses to sell at a loss rather than risk additional depreciation.
I used a variety of tools to statistically examine these trends. The overall trend and patterns in 'Price Disparity' were first observed using descriptive statistics. This assisted in identifying any systematic bias in the investor's decisions, offering a comprehensive picture of the investor's investment behavior.
Following that, I utilized inferential statistics, such as t-tests and ANOVA, to see whether these patterns were statistically significant. The investigation focused on identifying any major bias in investment decisions by analyzing the 'Price Disparity' while purchasing and selling.

Results:

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
Price Disparity
Trade Date
6
4
2
0
−2
−4
−6
2020-01
2020-05
2020-09
2021-01
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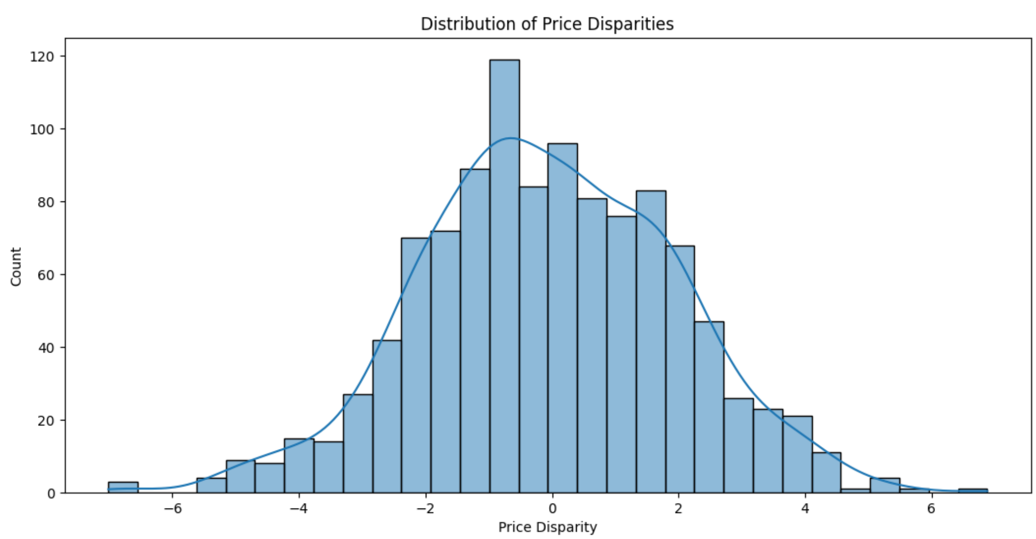
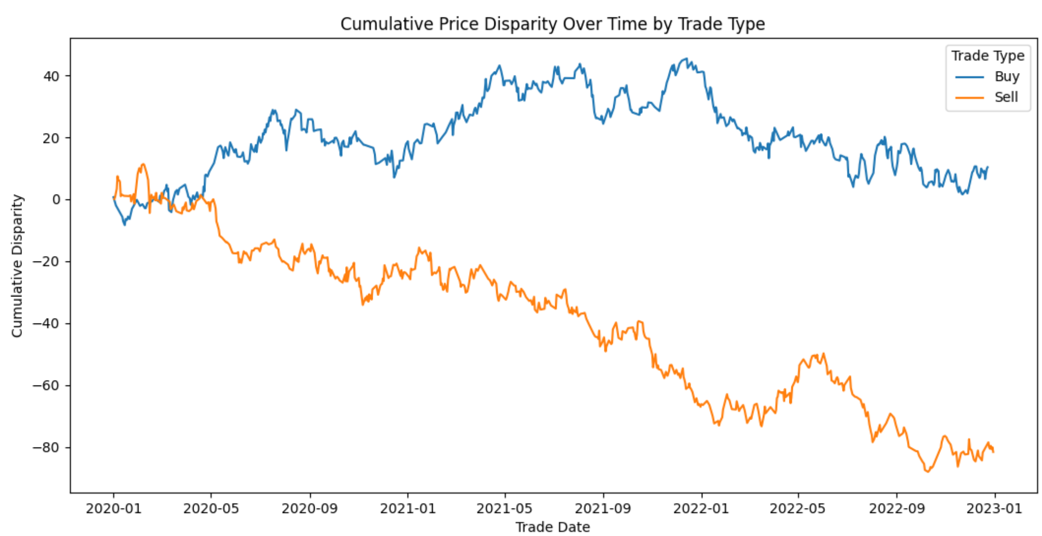
2022-09
2023-01


Distribution of Price Disparities
Count
Price Disparity
120
100
80
60
40
20
0
−6
−4
−2
0
2
4
6



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.

Conclusion:

In conclusion, the data suggest that cognitive biases play a significant role in the decision-making process of investors. I was able to uncover these biases within a synthesized data context through this work, providing useful insights that could drive future investing strategies. By understanding these trends, an investor can try to mitigate these biases, potentially leading to more effective long-term investing outcomes.

The adoption of a reinforcement learning algorithm could improve this process even further by learning from prior investment decisions to guide future behavior and lessen the impact of cognitive biases. It is critical to highlight that the construction of such an algorithm would need to be tailored, taking into account the unique investment behavior and patterns displayed by each investor.