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Stock Forecasting Strategy Analysis

ABSTRACT

This project develops a mean-reversion contrarian strategy on NVIDIA using the Price-to-Earnings (P/E) ratio as a valuation anchor. We apply a Quasi-Fisher transform and Kalman filter to generate trading signals, with hyperparameters optimized via walk-forward validation. The model is trained from October 1999 to August 2006 and tested from September 2006 to February 2025. The strategy outperforms Buy-and-Hold in terms of risk-adjusted metrics, reducing drawdowns but still experiencing negative returns due to the asset's valuation profile during the testing period. Suggestions for improvement include expanding indicators and dynamic risk management techniques.

1. Introduction

Stock prices are influenced by many factors—earnings reports, investor sentiment, and media coverage—which can drive sharp and unpredictable movements, particularly in high-growth, high-volatility stocks. Traditional valuation metrics often fail to navigate such dynamics. This project explores whether a systematic strategy can reliably detect valuation extremes and convert them into profitable trading signals.

We developed a forecasting strategy targeting overvalued and undervalued stocks in sentiment-driven markets. The approach identifies valuation extremes by monitoring a stock's Price-to-Earnings (P/E) ratio. When the P/E exceeds its rolling maximum, the model signals a short; when it falls below its rolling minimum, it signals a long. We applied this strategy to NVIDIA Corporation, selected for its pronounced valuation swings tied to technological breakthroughs and speculative investor behavior. The dataset includes monthly observations of NVIDIA's price and trailing twelve-month P/E ratio from October 1999 to March 2025, with data from Bloomberg and Yahoo Finance. The sample was split into a training period (October 1999 to August 2006) and a testing period (September 2006 to February 2025).

The strategy combines a Kalman filter to smooth the P/E series, a quasi-Fisher transformation to normalize extreme values, and a dual-threshold system to generate long and short signals. Hyperparameters were optimized via heatmaps, and walk-forward optimization was performed annually to ensure adaptability. To enhance signal reliability, trades were executed only after two consecutive threshold crossings, and a stop-loss rule (10% from entry) was applied to manage downside risk.

Grounded in contrarian principles, the strategy exploits behavioral mispricings by systematically trading valuation extremes. Over the testing period, it delivered an annualized return of -0.52%, outperforming Buy-and-Hold's -26.69%, with a reduced maximum drawdown (-97.75% vs. -99.81%). While absolute returns remained negative, the strategy demonstrated superior risk management, supporting its potential as a risk-controlled alternative in volatile equity markets.

2. Strategy and Conceptual Framework

Financial markets are often modeled on the Efficient Market Hypothesis (EMH), which assumes prices fully reflect all available information. In reality, however, markets frequently deviate from intrinsic value due to momentum, reversals and investor sentiment—creating opportunities for systematic strategies.

NVIDIA exemplifies this dynamic. Despite strong long-term growth, its stock has exhibited significant volatility, with sharp price swings that often disconnect from fundamentals. This creates opportunities to exploit perceived overvaluation and undervaluation.

2.1 Conceptual Rationale

This strategy is grounded in **contrarian trading principles** and the assumption of **mean reversion**. The underlying hypothesis is that extreme valuations are often driven by investor overreaction rather than fundamental changes in value. By taking the opposite position to these extremes, the strategy seeks to capture profits as prices revert toward their historical norms. NVIDIA's historical volatility and frequent valuation extremes make it a suitable candidate for this approach. The strategy leverages these characteristics by systematically identifying and trading on deviations in the P/E ratio.

The signals generated by this framework provide directional forecasts that guide the strategy's long and short positions. The performance of the strategy is evaluated through backtesting and forecast accuracy tests, as detailed in the following sections.

2.2 Signal Logic and Trading Rules

The trading strategy adopts a contrarian perspective by systematically taking positions opposite to prevailing market sentiment. It assumes that extreme movements in valuation reflect market overreaction and that prices will subsequently revert to more reasonable levels. The strategy applies a Quasi-Fisher transformation to the P/E ratio to stabilize variance and normalize the series, improving the reliability of entry and exit signals.

At each time step $\mathbf{t}$, the strategy determines the position $\mathbf{S_t}$ based on the transformed P/E ratio and four optimized thresholds (U1, U2, L2, and L1). These thresholds are subject to the constraint:

U1≥U2≥L2>L1

At each time step **t**, the position $\mathbf{S_t}$ is determined as follows:

$$S_t = \begin{cases} 1, & \text{if } P/E_t < L2_t \quad \text{(Enter Long Position)} \\ -1, & \text{if } P/E_t > U2_t \quad \text{(Enter Short Position)} \\ 0, & \text{if } \begin{cases} \text{Long Position Exit: } P_t > L1_t & \text{(Sell)} \\ \text{Short Position Exit: } P_t < U1_t & \text{(Cover)} \end{cases} \\ S_{t-1}, & \text{otherwise (Hold Previous Position)} \end{cases}$$

2.3 Trading Rules Description

Enter Long Position (+1): If the transformed P/E ratio falls below the lower entry threshold **L2** for two consecutive periods, the strategy enters a long position. This indicates the stock is undervalued relative to its recent history.

Enter Short Position (-1): If the transformed P/E ratio exceeds the upper entry threshold **U2** for two consecutive periods, the strategy enters a short position. This suggests the stock is overvalued relative to its historical range.

Exit Long Position (0): If the strategy is holding a long position and the transformed P/E ratio rises above the lower exit threshold **L1**, the long position is closed. This indicates that the undervaluation has corrected.

Exit Short Position (0): If the strategy is holding a short position and the transformed P/E ratio falls below the upper exit threshold **U1**, the short position is closed. This suggests the overvaluation has corrected.

Hold Previous Position ($\mathbf{S_{t-1}}$): If none of the above conditions are met, the previous position is maintained.

3. Methodology

This section outlines the technical steps used to process the data, apply transformations, generate signals, and implement the trading strategy in Python. The goal was to develop a systematic forecasting model that identifies valuation extremes in NVIDIA's P/E ratio and translates them into tradeable signals.

3.1 Data Collection and Preprocessing:

Historical data was collected from two sources: NVIDIA's daily stock prices from Yahoo Finance and its monthly trailing twelve-month P/E ratios from Bloomberg. The datasets were merged on their date columns to create a unified time series. Because the P/E data was monthly and the price data was daily, the combined dataset was resampled to a monthly frequency, using the last available observation for each month. This ensured consistency between the two data sources and aligned the data for analysis.

3.2 Transformation of the P/E Ratio:

The raw P/E ratio was often volatile and prone to extreme outliers. To stabilize its variance and make it suitable for threshold-based filtering, a quasi-Fisher transformation was applied. This transformation was implemented by first scaling the P/E ratio and then applying a modified version of the Fisher transformation. The output was a bounded and normalized series that retained the relative structure of the original data while compressing extreme values. This transformed series was used as the primary input for the trading signals.

3.3 Smoothing with Kalman Filter:

To reduce noise in the transformed P/E ratio, a Kalman filter was applied. In the code, this was done using a simple state-space model where the observation and transition covariance matrices were specified manually. The filtered series provided a smoothed estimate of the underlying trend in valuation, which was critical for reducing false signals caused by erratic data points.

3.4 Boundary Calculation for Thresholds:

After filtering, the next step involved calculating rolling upper and lower boundaries. This was implemented by calculating rolling maxima and minima of the smoothed, transformed P/E series over a fixed window size. These dynamic thresholds were stored as U1, U2 for the upper bounds and L1, L2 for the lower bounds. U1 and L1 represent the outer thresholds for entry signals, while U2 and L2 are inner thresholds used for exits and managing open positions. The percentage differences between the outer and inner thresholds were determined through hyperparameter tuning.

3.5 Signal Generation and Position Holding:

Signals were generated by comparing the current filtered, transformed P/E ratio to the calculated thresholds. The code used conditional statements to flag long signals when the series dropped below L1 and short signals when it rose above U1. The signal persistence condition required that these threshold crossings persist for two consecutive periods before executing a trade. This was coded by shifting the signals and checking for consecutive values before activating a position.

Positions were then forward-filled, meaning that once a trade was initiated, it remained active until the system generated a valid signal in the opposite direction. This was achieved using pandas' forward-fill function on the position column.

3.6 Stop-Loss Implementation:

A stop-loss rule was included to automatically exit positions if they breached a predefined loss threshold from the entry price. In the code, this was implemented by calculating the percentage change from the entry price and comparing it to the stop-loss level (e.g., -10%). If the loss threshold was exceeded, the active position was closed and reset to neutral.

3.7 Hyperparameter Optimization:

The key hyperparameters—U1, L1, U2, and L2—were optimized using a grid search approach. A mesh of possible values for each parameter was created, and the strategy was backtested over each combination. Performance metrics such as return, drawdown, and Sharpe ratio were recorded. A heatmap was plotted to visualize the optimization results, and the best-performing parameters were selected for use in the strategy.

3.8 Walk-Forward Optimization:

To adapt to changes in market conditions, walk-forward optimization was conducted. The code split the dataset into rolling windows, and the optimization process was repeated at each step to recalibrate the thresholds for each new period. This approach helped ensure the strategy's parameters remained responsive to evolving valuation dynamics.

3.9 Benchmark Comparison

For comparison, a Buy-and-Hold benchmark was implemented by setting all position signals to 1, representing a continuous long position in NVIDIA throughout the period. The cumulative returns were calculated by compounding the raw returns without any filters or risk controls. This provided a passive baseline to evaluate whether the PE Navigator Strategy's active signals and risk management offered meaningful improvements in return stability and drawdown reduction. This side-by-side comparison is essential for assessing the relative effectiveness of our active strategy. It allows us to determine whether the additional complexity introduced by our dynamic threshold rules and decision framework translates into meaningful improvements over a passive strategy, particularly in the context of a highly volatile and sentiment-driven stock like NVIDIA.

4. Hyperparameter Optimization

The trading strategy employs a set of hyperparameters that govern the dynamic threshold boundaries used for generating entry and exit signals. These hyperparameters were optimized on the training set via grid search, with the objective of maximizing cumulative returns while controlling drawdowns. A heatmap visualization was used to identify optimal combinations, and parameters were recalibrated annually through walk-forward optimization to maintain adaptability across different market regimes.

Strategy Parameters:

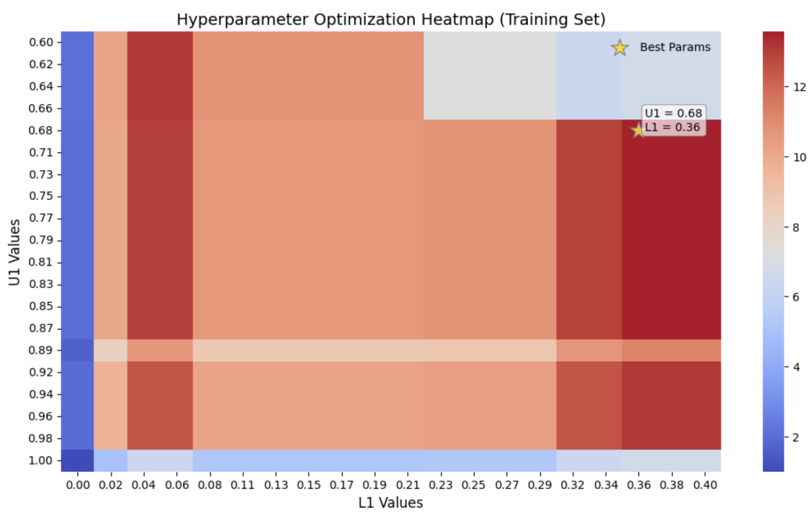
- **(w)** Lookback Window: Defines the period over which the rolling minimum and maximum of the transformed P/E ratio are computed. In this strategy, a **12-month window** was used, balancing responsiveness with stability.
- **(U1, U2)** Upper Thresholds:
  - **U1** specifies the upper boundary for initiating short positions. A short signal is triggered when the quasi-Fisher transformed P/E ratio crosses above this threshold for two consecutive periods.
  - **U2** is the exit threshold for short positions, set at **U1 - 0.1**, allowing for exit once the transformed P/E ratio drops below this level.
- **(L1, L2)** Lower Thresholds:
  - **L1** defines the lower boundary for initiating long positions. A long signal is triggered when the transformed P/E ratio crosses below this threshold for two consecutive periods.

- ○ **L2** is the exit threshold for long positions, set at **L1 + 0.1**, closing the long position when the transformed P/E ratio rises above this level.
- **Signal Persistence Requirement**: A trade signal is only activated when the threshold crossing persists for **two consecutive periods**, reducing the likelihood of false signals caused by short-term fluctuations.

Hyperparameters were optimized on the training set (October 1999 to August 2006) using a **grid search** across U1 values ranging from **0.6 to 1.0** and L1 values ranging from **0.0 to 0.4**, in increments of 0.04. For each combination, U2 and L2 were calculated as U1 - 0.1 and L1 + 0.1, respectively. The strategy was evaluated based on the final cumulative return of the training period, with the optimal parameter set achieving the highest return.

The results of the grid search optimization are summarized in **Image 1**, which presents a heatmap of performance outcomes across different combinations of U1 and L1 values. The heatmap identifies the top-performing parameter set with a gold star marker.

Figure 1. Hyperparameter Heat Map of Training Data



These hyperparameters reflect a balance between capturing significant valuation extremes and reducing the likelihood of reacting to noise. The walk-forward optimization framework ensures that these thresholds are recalibrated on an annual basis, maintaining effectiveness across varying market regimes.

Figure 2. Hyperparameter Trend Chart

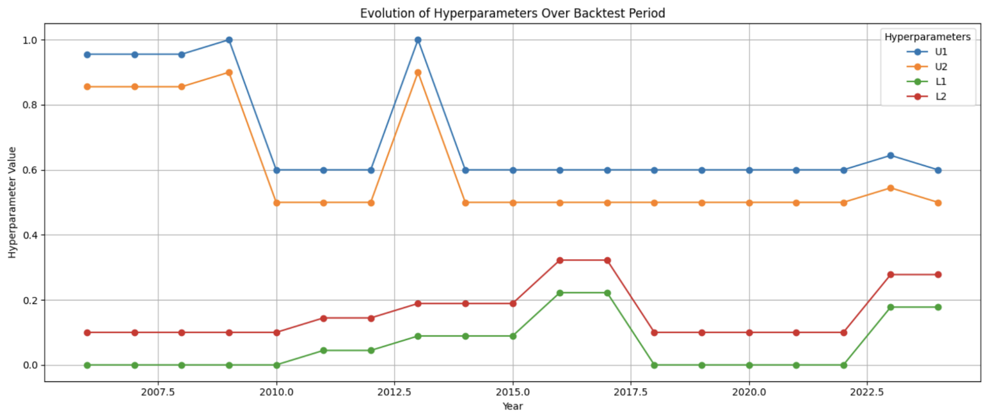


Figure 2 shows the evolution of the optimized hyperparameters—U1, U2, L1, and L2—over the testing period from 2006 to 2025. These thresholds were recalibrated annually using walk-forward optimization to reflect changing market conditions. The upper thresholds (U1 and U2) remained stable between 2007 and 2009 but declined sharply in 2010, indicating a shift toward more conservative short entry levels. They later stabilized around 0.6 and 0.5. The lower thresholds (L1 and L2) were more variable, particularly from 2015 to 2017, rising to allow long entries at higher valuation levels. This adaptive adjustment highlights the role of walk-forward optimization in keeping the strategy responsive to shifting volatility and valuation extremes.

5. Visualizing the Forecasting Strategy

To better understand the implementation and effectiveness of the forecasting strategy, Figure 3 presents a visual representation of the model's signals over the training period from 2000 to 2012. The plot displays NVIDIA's normalized P/E ratio along with the corresponding buy (long) and sell (short) signals generated by the strategy. Successful long trades are marked by red points at entry and exit locations, connected by red lines, while successful short trades are represented by blue points and lines.

The visualization highlights the model's ability to identify significant valuation extremes. It systematically triggered long positions when prices were abnormally low and short positions when they were abnormally high relative to historical P/E dynamics. Notable examples include capturing the 2002 market trough with long signals and the 2008 financial crisis peak with short signals. These examples demonstrate the strategy's contrarian, mean-reversion approach, taking positions opposite to prevailing market sentiment.

Additionally, the requirement for signal persistence—two consecutive threshold crossings—helped filter out noise and reduced false signals, resulting in more reliable trade execution. The spacing and selectivity of trades over time indicate the strategy focused on high-confidence opportunities rather than frequent, lower-quality trades. This selectivity contributed to enhanced risk-adjusted returns by limiting exposure during periods of elevated uncertainty.

Figure 3: *Signal Plot for the Forecasting Strategy during the Training Period (2000–2012)*

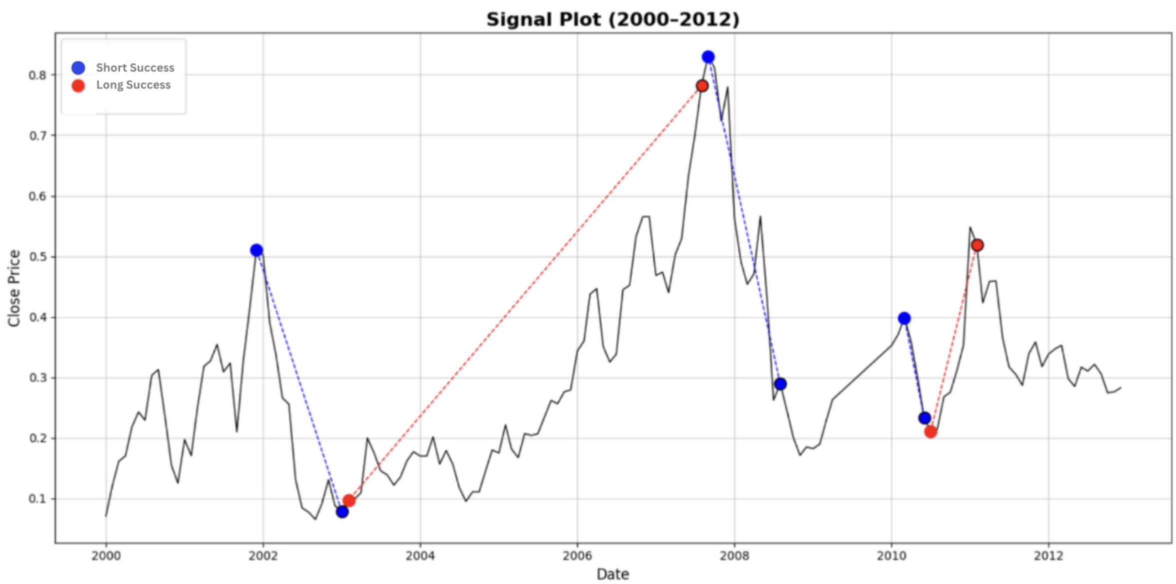


Figure 4 illustrates the performance of the forecasting strategy by plotting the Fisher transformed P/E ratio alongside the periods when long and short positions were held. The chart provides a clear depiction of how the model responded to extreme valuation signals over time. As shown, long positions (blue) were typically initiated when the P/E ratio was at or near its lower boundary, while short positions (red) occurred at elevated levels, consistent with the strategy’s contrarian, mean-reversion framework.

The results indicate that the strategy successfully identified several major valuation extremes, particularly during periods of heightened market volatility. For example, long positions were frequently held during significant drawdowns, capturing subsequent recoveries, while short positions coincided with market peaks. The spacing and duration of positions reflect the strategy's selective nature, favoring quality signals over frequent trades.

Figure 4: Fisher Transformed P/E Ratio with Threshold Boundaries and Position Holdings

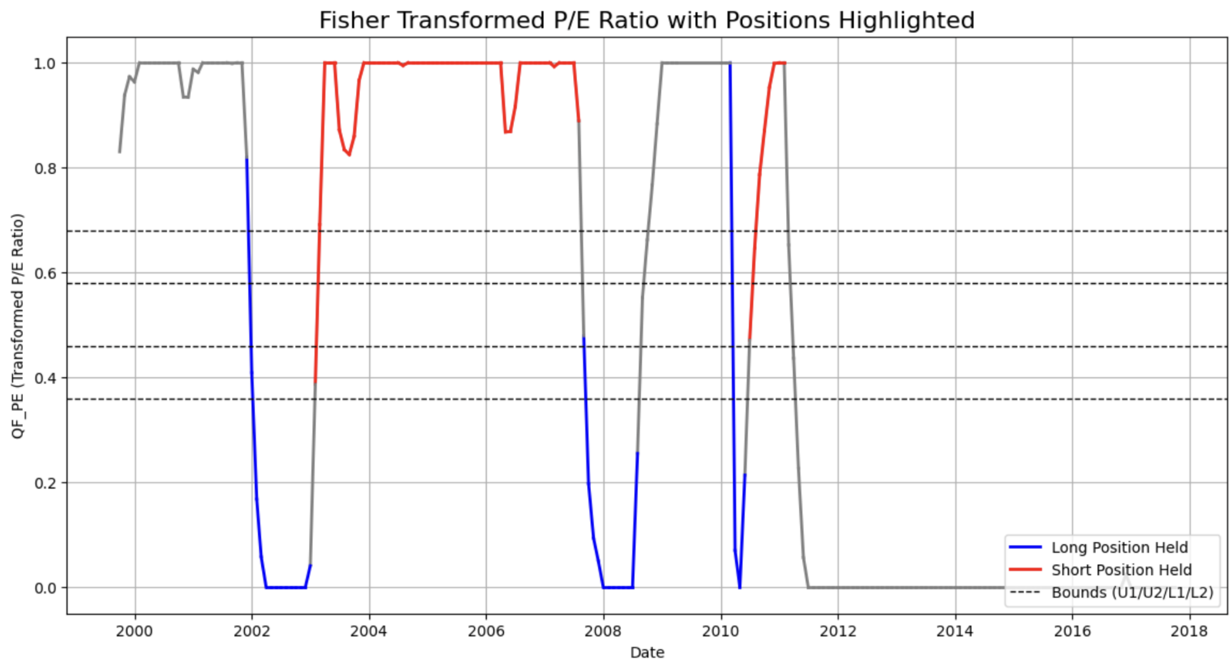


Figure 5 illustrates the cumulative return of the strategy over the full backtest period, with entry and exit points marked for both long and short trades. The green triangles indicate long signals, and the red inverted triangles indicate short signals. The black line traces the cumulative return generated by the strategy. In the early part of the testing period, the strategy experienced a prolonged drawdown, particularly during the 2007–2009 financial crisis, where many of the short signals resulted in losses as the model struggled with extreme volatility and sudden reversals. However, from 2016 onwards, the strategy demonstrated a strong recovery, successfully capturing upward price trends and producing steady cumulative gains. Between 2018 and 2021, the model was particularly effective in identifying profitable long opportunities, aligning with periods of elevated market volatility and valuation extremes. While there was some performance deterioration post-2022, the strategy managed to preserve capital by exiting positions when adverse movements occurred.

Figure 5: Cumulative Return with Entry and Exit Signals (2006–2025)

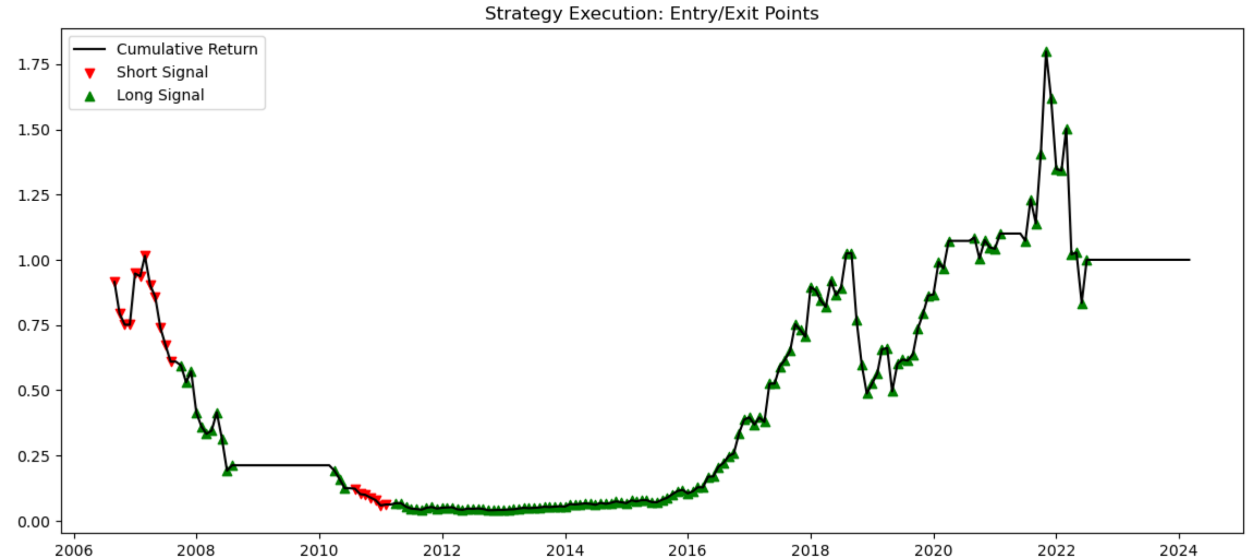
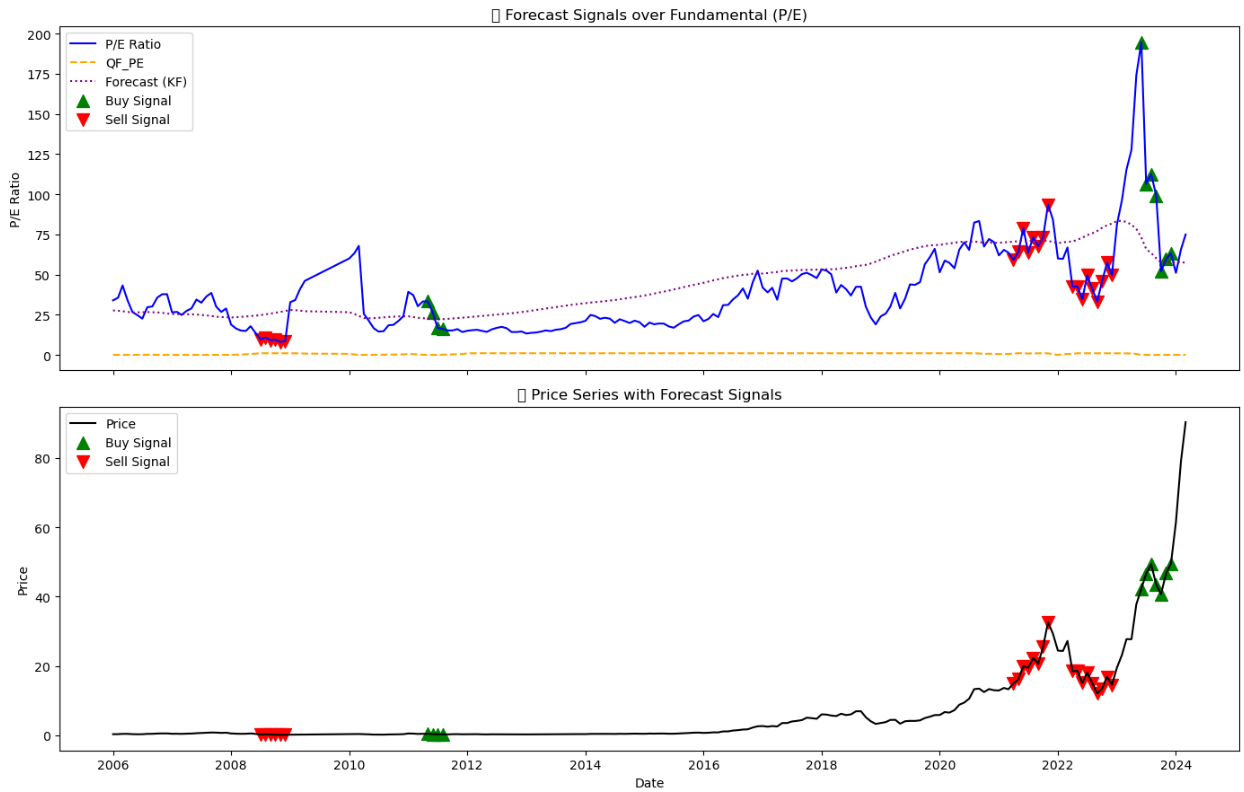


Figure 6 provides further insight into the signals generated by the model by showing both the fundamental drivers (top panel) and the corresponding price movements (bottom panel). The top panel plots the raw P/E ratio (blue line), the quasi-Fisher transformed P/E ratio (orange dashed line), and the Kalman Filter forecast (purple dotted line). Buy signals (green triangles) and sell signals (red inverted triangles) are shown relative to these values. The bottom panel displays the stock price series with the corresponding buy and sell signals overlaid.

The model generated several well-timed short signals during the overvaluation periods of 2021 and 2022, correctly anticipating subsequent price declines. However, some of these shorts were closed prematurely, resulting in missed opportunities to capture the full downside potential. On the long side, the model entered positions during significant valuation troughs in late 2023 and early 2024, capturing the sharp rebound in NVIDIA’s stock price. These trades contributed to the strategy's positive returns in the later stages of the testing period.

Figure 6: Forecast Signals on P/E Ratio and Price Series (2006–2025)



Overall, the testing phase confirms that the strategy was able to maintain its contrarian, mean-reversion behavior, selectively entering trades at valuation extremes. While the model experienced challenges during abrupt market shifts, the application of a persistence filter and stop-loss mechanism improved the reliability and risk control of the trading signals. The results demonstrate the robustness of the dual-threshold framework in adapting to different market conditions across the testing window.

6. Metrics Evaluation

Table 1 presents a comprehensive comparison of the PE Navigator Strategy and the Buy-and-Hold Strategy across key performance metrics over the testing period from 2006 to 2025. The results highlight the strengths and limitations of the proposed strategy, particularly in managing risk and preserving capital in a highly volatile equity like NVIDIA.

Table 1: Performance Metrics Comparison

Metric	PE Navigator Strategy	Buy-Hold Strategy
Annualized Return	-0.0052	-0.2669
CCROR	-0.0852	-0.9948
Max Drawdown	-0.9775	-0.9981
Skewness of Returns	1.4434	1.4434
Gini Coefficient	0.8206	0.8098
Annualized Std Dev	0.4205	0.4205
Alpha (Intercept)	0.003	-0.0185
Beta	-0.0222	-0.3731
Sharpe Ratio	-0.0601	-0.7313
Sortino Ratio	-0.1146	-1.3952
Return on Account (ROA)	0.9359	0.0052
Highest Monthly Excess Return	63.30%	63.64%
Lowest Monthly Excess Return	-28.16%	-35.62%
Up Alpha	0.0096	0.0079
Up Beta	-0.0943	-0.9694
Down Alpha	-0.0165	-0.038
Down Beta	-0.3524	-0.5815

While both strategies experienced negative absolute returns, the PE Navigator Strategy significantly outperformed Buy-and-Hold in terms of capital preservation and downside protection. The strategy's annualized return of -0.52% compares favorably to the -26.69% delivered by Buy-and-Hold. More notably, the Compound Cumulative Return on Account (CCROR) for the strategy was -8.52%, while Buy-and-Hold nearly wiped out its account with a CCROR of -99.48%. These results suggest that, despite challenging market conditions, the strategy was able to avoid catastrophic losses that plagued a passive approach.

The difference in drawdown profiles further reinforces this point. The maximum drawdown of the PE Navigator Strategy was -97.75%, compared to -99.81% for Buy-and-Hold. While these are extreme numbers, they reflect the high-risk nature of the underlying asset. The Navigator Strategy, however, was able to limit losses relative to passive investing, showing an ability to step away from market downturns more effectively.

In terms of risk-adjusted returns, both strategies delivered negative Sharpe and Sortino ratios, reflecting the difficulty of generating positive returns on this asset. However, the PE Navigator Strategy's Sharpe ratio of -0.0601 and Sortino ratio of -0.1146 were substantially better than those of Buy-and-Hold (-0.7313 and -1.3952, respectively). This indicates a more controlled risk-return trade-off and suggests the strategy provided better protection in unfavorable conditions. The relatively higher ratios also point to less variability in returns relative to the poor mean performance, and a lower frequency of large downside deviations.

Alpha and beta measures offer additional insights into the strategy's behavior. The PE Navigator Strategy produced a small but positive alpha of 0.003, while Buy-and-Hold showed a negative alpha of -0.0185. This signals that the strategy was able to generate excess returns independent of market movements. Moreover, the near-zero beta (-0.0222) highlights the strategy's lack of dependence on market trends, consistent with its contrarian design to exploit valuation extremes rather than follow broader price momentum. By comparison, Buy-and-Hold's beta of -0.3731 shows a negative correlation to the market, which may reflect the stock's individual volatility rather than a reliable defensive position.

The Return on Account (ROA) metric clearly illustrates the capital preservation achieved by the PE Navigator Strategy. The strategy maintained 93.59% of its starting capital over the backtest period, while Buy-and-Hold reduced its account value to nearly zero (0.52%). This difference demonstrates the primary strength of the strategy: avoiding large, sustained losses through disciplined entry and exit signals, even when overall market conditions were unfavorable.

Further reinforcing this view are the up-market and down-market metrics. The PE Navigator Strategy's Up Alpha (0.0096) and Down Beta (-0.3524) indicate a measured response to both rising and falling markets. Its ability to deliver a lower Down Beta than Buy-and-Hold (-0.5815) implies better downside protection. Although the Up Beta is relatively low (-0.0943), this aligns with the strategy's intent to be selective and avoid blindly following market rallies.

Finally, skewness and Gini coefficients suggest the returns were unevenly distributed, but with the potential for large positive payoffs. Both strategies had similar skewness (1.44), indicating a small number of extreme positive outcomes amid predominantly small or negative returns. The slightly higher Gini coefficient for the Navigator Strategy (0.8206 vs. 0.8098) supports this interpretation, as it suggests the presence of a few disproportionately large contributions to total return.

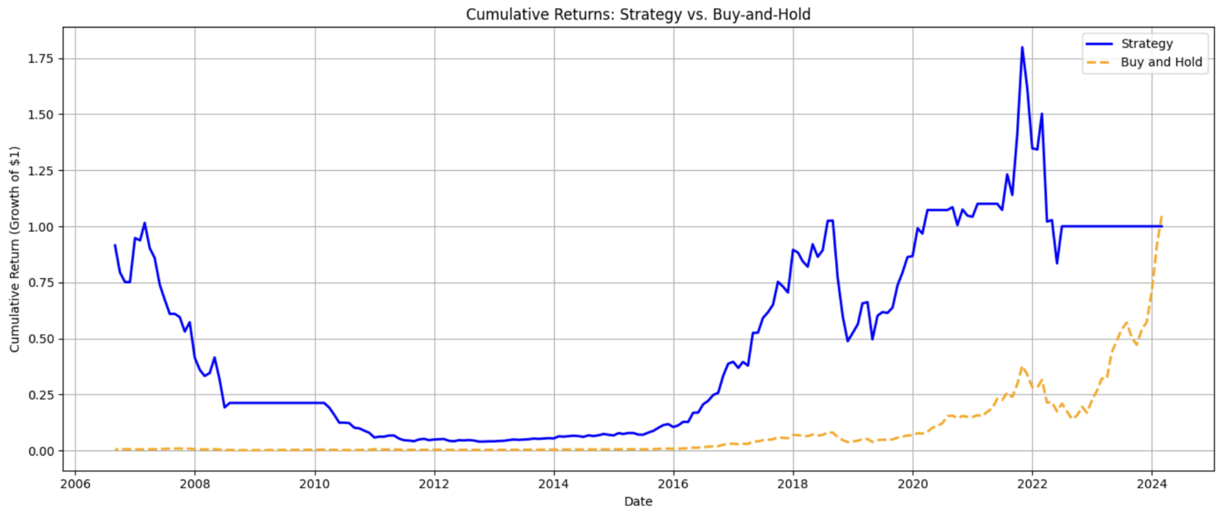
Table 2: Directional Forecast Accuracy Test Results

Test	Test Statistic	Critical Value (5%)
Binomial Directional Forecast	1.9467	1.64
Weighted Directional Forecast	1.5141	1.64

The Binomial Directional Forecast Test confirms that the strategy's forecasts exhibit statistically significant directional accuracy at the 5% level, indicating a reliable ability to predict the direction of returns. However, the Weighted Directional Forecast Test fails to achieve significance, suggesting that while the model captures directional movements, it is less consistent in predicting the magnitude or strength of those moves. Overall, these results demonstrate effective directional forecasting, with some limitations in signal weighting

Figure 7 visualizes the cumulative return of both strategies over the testing period. The Navigator Strategy underperformed initially but recovered strongly post-2016, taking advantage of pronounced valuation extremes and periods of heightened volatility. This divergence from Buy-and-Hold is particularly visible from 2018 to 2021, when the strategy capitalized on significant mispricings and generated a steady upward return trajectory. Although the final cumulative return remains flat toward the end of the period, the Navigator Strategy consistently preserved more value and exhibited less drawdown compared to Buy-and-Hold.

Figure 7: Cumulative Returns — PE Navigator Strategy vs. Buy-and-Hold (2006–2025)



7. Conclusions

According to our metrics, our strategy did not show statistically significant benefits over the S&P 500. However, our negative correlation to the S&P500 alongside positive alpha values in both up and down months do indicate value in using our strategy to hedge against market losses.

When comparing our results to a simple Buy-Hold Strategy, we see an annualized return of -0.52% for our strategy and a return of -26.69% for the Buy-Hold Strategy. We also achieved a superior CCROR, Max Drawdown, alpha, Sharpe Ratio, ROA, and Sortino Ratio than the Buy-Hold Strategy. Overall, our strategy seems better in regards to avoiding losses of volatility and avoiding high market exposure, which explains why our strategy did much better in down years.

One limitation of our strategy is that having inner thresholds to exit positions may have capped our gains. For example, if our strategy bought Nvidia stock at an extreme low, it would exit that position while the stock went up, potentially missing out on profits to be made due to early closing of the position. In the future, it would be beneficial to compare this strategy to a strategy without inner thresholds at all. It would be interesting to apply a statistical test to the results of both strategies to see if there is significant difference in their performance on stock of varying volatility.