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The Power Of Price Action Reading

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Abstract

Evaluating the effectiveness of technical analysis has always been a challenging task. Translating each technical pattern into a quantifiable measure is often unfeasible, leading to the perception of technical analysis as more art than science. Proving its utility rigorously remains elusive. This study aims to investigate the value added by incorporating discretionary technical trading decisions within the context of stocks experiencing significant overnight gaps. By creating a bias-free simulated trading environment, we assess the profitability improvement of a simple automatic trading strategy when supported by an experienced technical trader. The trader's role is to restrict the algorithm to trade only those stocks whose daily charts appear more *promising*. Additionally, we conduct a test where the experienced trader micromanaged the open positions by analyzing, in a bias-free environment, the daily and intraday price action following the overnight gap. The results presented in this paper suggest that discretionary technical trading decisions, at least when conducted by a skilled trader, may significantly enhance trading outcomes, transforming seemingly unprofitable strategies into highly performing ones. This paper provides empirical evidence supporting the integration of discretionary judgment with systematic trading approaches, offering valuable insights for enhancing trading outcomes in financial markets.

Keywords: *Momentum, Swing Trading, Day Trading, Technical Analysis, Overnight Gaps, Gaps, Gap&Go, Algorithmic Trading, Risk Management*

1 Introduction

Stock price gaps, defined as significant discontinuities in price from one trading session to the next, are a prevalent and impactful phenomenon in financial markets. These gaps, often driven by substantial news events, earnings reports, economic indicators, or geopolitical developments, can lead to heightened volatility and uncertainty. Understanding the behavior of stocks following such gaps is crucial for traders and investors aiming to develop effective trading strategies.

Significance of Stock Price Gaps

Why do stock price gaps matter? They have the potential to signal substantial changes in market sentiment and future price movements. A gap up, where a stock opens significantly higher than its previous closing price, typically reflects positive market sentiment or favorable news. Conversely, a gap down indicates negative sentiment or adverse news. Predicting the subsequent behavior of stocks after these gaps can offer traders a competitive edge in capitalizing on market movements.

Challenges in Predicting Post-Gap Behavior

Despite extensive research, predicting the post-gap behavior of stocks remains a complex and challenging task. Traditional studies employ various technical and fundamental analysis techniques. Technical analysis examines historical price charts and patterns, while fundamental analysis focuses on the underlying financial health and performance of companies. However, one critical component often overlooked is trader intuition, a less quantifiable but potentially significant factor.

The Role of Trader Intuition

Trader intuition, the ability to make decisions based on experience and instinct, is crucial in discretionary trading. Unlike algorithmic trading, which relies on predefined rules and mathematical models, discretionary trading leverages the trader's judgment and perception of market conditions. Intuition in trading encompasses recognizing patterns, assessing market sentiment, and making rapid decisions amid uncertainty. Experienced traders often develop a *gut feeling* that can enhance their trading performance.

Study Aim

This study aims to investigate the impact of discretionary trading decisions on stocks that gap up more than 6% overnight. We create an unbiased experimental setup by anonymizing charts, stripping away specific dates, ticker symbols, sectors, news, specific prices, and volumes. The sole basis for decision-making was the visual inspection of historical price behavior over a two-year price history isolating the effect of trader intuition.

Our primary objective is to evaluate how a discretionary trader, uninfluenced by external information, performs in selecting trades purely from a price pattern perspective. By focusing solely on historical price behavior, we aim to understand how intuition and experience contribute to trading success. Additionally, we introduce a micromanagement layer to assess its effect on trading performance. This involves meticulous position management, including setting precise entry points, stop losses, and executing partial exits at predetermined intervals.

Study Implications

Our findings suggest that discretionary technical trading, complemented with structured micromanagement, can significantly enhance trading outcomes. This paper delves into the methodology, results, and implications of our study, offering valuable insights into the role of trader intuition and the potential benefits of a hybrid trading approach that blends discretionary judgment with systematic management techniques. By providing empirical evidence on intuition-driven trading's effectiveness, we contribute to the broader understanding of trading strategies and their practical applications in financial markets.

Paper Structure

This paper is organized as follows: in Section 2, we provide a brief literature review. In Section 3, we discuss how we built the database. In Section 4, we present the results of our analysis and introduce the software deployed to include discretionary trading decisions within this empirical investigation. In Section 5 we conclude.

2 Literature Review

The study of stock price gaps has been a focal point for financial researchers and traders, as these gaps often signal significant market movements and potential trading opportunities. A price gap occurs when a stock opens at a price significantly different from its previous closing price, typically due to news events or other external factors. Understanding the behavior of stocks after such gaps can provide valuable insights for traders and investors.

Stock Price Gaps and Their Implications

The early research of Oppenheimer and Schlarbaum (1981) delves into the causes and implications of stock price gaps. They categorize gaps into several types, such as *breakaway*, *runaway*, and *exhaustion gaps*, each possessing distinct predictive qualities regarding future price movements. Their findings suggest that *breakaway gaps* often signify the beginning of a new trend, while *exhaustion gaps* may indicate the end of a trend. This categorization provides a foundation for subsequent research into the predictive power of price gaps.

Bulkowski (2005) further expandes on this work by offering comprehensive analyses of chart patterns, including gaps. His research confirms that certain types of gaps could serve as reliable indicators of future price movements, thus offering valuable trading opportunities. Bulkowski's work is widely cited in technical analysis literature, emphasizing the importance of understanding gap types and their implications.

Post-Earnings Announcement Drift (PEAD)

Post-Earnings Announcement Drift (PEAD) is a well-documented anomaly in financial markets where stock prices continue to drift in the direction of an earnings surprise for some time following the earnings announcement. This phenomenon has been extensively studied and provides insights into the behavior of stocks that experience significant price gaps due to earnings reports.

Ball and Brown (2013) are among the first to document the PEAD phenomenon, finding that stocks with positive earnings surprises tend to experience a prolonged period of abnormal returns following the announcement. This drift can last from several weeks to several months, indicating that the market does not fully incorporate the new information immediately.

Subsequent research by Bernard and Thomas (1989) reinforces these findings, suggesting that the delayed market reaction could be attributed to investor underreaction to earnings news. Their study shows that stocks with positive earnings surprises continue to outperform, while those with negative surprises underperform, even after the initial announcement period.

The PEAD phenomenon is particularly relevant to the study of stock price gaps, as earnings announcements are a common catalyst for such gaps. Stocks that gap up significantly on positive earnings news may exhibit similar post-announcement drift, leading to continue price appreciation or plateauing over time.

Discretionary vs. Algorithmic Trading

The debate between discretionary and algorithmic trading has been extensively covered in financial literature. Discretionary trading relies on the trader's experience, intuition, and ability to make real-time decisions. Studies by Lo et al. (2000) highlight the significant role of technical analysis in trading performance. Their research found that pattern recognition and subjective judgment in technical analysis can provide a competitive edge in volatile markets. This finding is supported by Fenton-O'Creevy et al. (2011), who investigate the role of emotions and intuition in trading. Their study concludes that high-performing traders effectively integrate emotional regulation and intuitive judgment, enabling them to make more informed decisions under pressure.

Algorithmic trading, on the other hand, utilizes automated systems to execute trades based on predefined rules and models. Aldridge (2013) discusses the advantages of algorithmic trading, including speed, consistency, and the ability to process large volumes of data. These systems can quickly adapt to new information and execute trades with precision, minimizing human errors. However, Hendershott et al. (2011) note that while algorithmic trading has become increasingly prevalent, it may lack the nuanced judgment provided by experienced discretionary traders. They argue that in highly uncertain or rapidly changing market conditions, discretionary trading can outperform algorithmic strategies.

The Role of Trader Intuition

Trader intuition, particularly in the context of decision-making under uncertainty, has been a topic of significant interest. Kahneman and Klein (2009) explore the conditions under which intuition can be reliable, emphasizing the importance of experience and pattern recognition. In financial markets, intuition often involves the ability to read historical price behavior and gauge market sentiment based on past experiences. Their work suggests that intuition, when grounded in extensive experience and expertise, can be a powerful tool in trading.

Sadler-Smith and Shefy (2004) further assert that intuitive decision-making is a critical component of expertise, especially in complex and dynamic environments like financial markets. Their research underscores the necessity of training and experience in developing reliable intuitive skills. They argue that intuitive judgment can complement analytical approaches, providing a more holistic perspective on market conditions.

Research into the cognitive processes behind trader intuition by Dane and Pratt (2007) also highlights how individuals develop intuitive expertise through repeated exposure to specific patterns and outcomes. They describe this process as *pattern recognition*, where traders, through experience, become adept at quickly identifying market signals and making rapid decisions.

Micromanagement in Trading

Micromanagement in trading refers to the detailed oversight of individual trades, including precise entry and exit points, stop losses, and profit-taking strategies. Tharp (2008) and Elder (2014) argue that effective micromanagement can significantly enhance trading performance by optimizing the risk-reward ratio and mitigating psychological biases. These authors advocate for a structured approach to trade management to improve consistency and outcomes.

Tharp (2008) emphasizes the importance of having a well-defined trading plan that includes specific rules for managing trades. This approach can help traders avoid emotional decision-making and stick to their strategy even during periods of market volatility. Elder (2014) supports this view, highlighting that micromanagement allows traders to adjust their positions dynamically in response to changing market conditions, thereby maximizing profits and minimizing losses.

Studies by Lo et al. (2000) highlight the importance of technical analysis in trading, which includes rigorous trade management techniques that can enhance profitability. Their research underscores the significance of systematic trade management in enhancing profitability and reducing the emotional impact of trading decisions.

Gaps in Existing Literature

While there is a substantial body of work on the predictive power of stock gaps, the role of discretionary trading and intuition within this context is less explored. Most research has focused on quantitative approaches and algorithmic trading systems. This study aims to bridge this gap by providing empirical evidence on the performance of a discretionary trader in an anonymized, unbiased setting, and by examining the impact of a structured micromanagement layer on trading outcomes. By contributing to the existing body of knowledge, this study offers practical insights for traders seeking to integrate discretionary elements and structured management techniques into their strategies.

3 Database

This study analyzes U.S. stocks listed on the NYSE and Nasdaq exchanges from January 1, 2016, to December 31, 2023. The dataset comprises approximately 7,000 stocks and is free from survivorship bias. The primary data source for these stocks is the Center for Research in Security Prices (CRSP). Intraday data at a 1-minute frequency for all stocks is sourced from IQFeed and Polygon. Notably, this intraday data is not adjusted for stock splits or dividends, ensuring that the database remains unaffected by retrospective price adjustments.

The objective of this research is to investigate the behavior of stocks around gap days. A gap event is considered in our database if the following criteria are satisfied:

1. **Significant Price Gaps**: An opening price at least 6% higher than the previous closing price.
2. **Minimum Price**: Stocks with a minimum opening price of $2.
3. **Minimum Pre-Market Trading Volume**: At least 200,000 shares traded in pre-market.

From the original dataset, we identify 9,794 events that satisfy our gap criteria.

4 Empirical Results

We first analyze 9,794 gaps from 2016 to 2023, focusing on the behavior of stock prices around the overnight gap. Results are exhibited in Figure 1.

Pre-Gap Behavior (-15 to -1 days)

In the fifteen days preceding a gap event, stock prices exhibit a gradual increase, starting from approximately -26% and moving towards 0%. This trend suggests a period of anticipatory buying or positive market sentiment. Traders likely position themselves ahead of expected positive news, contributing to a steady price rise. The progression from -26% to 0% indicates a systematic build-up in stock prices as market participants respond to signals and information that precede the gap event.

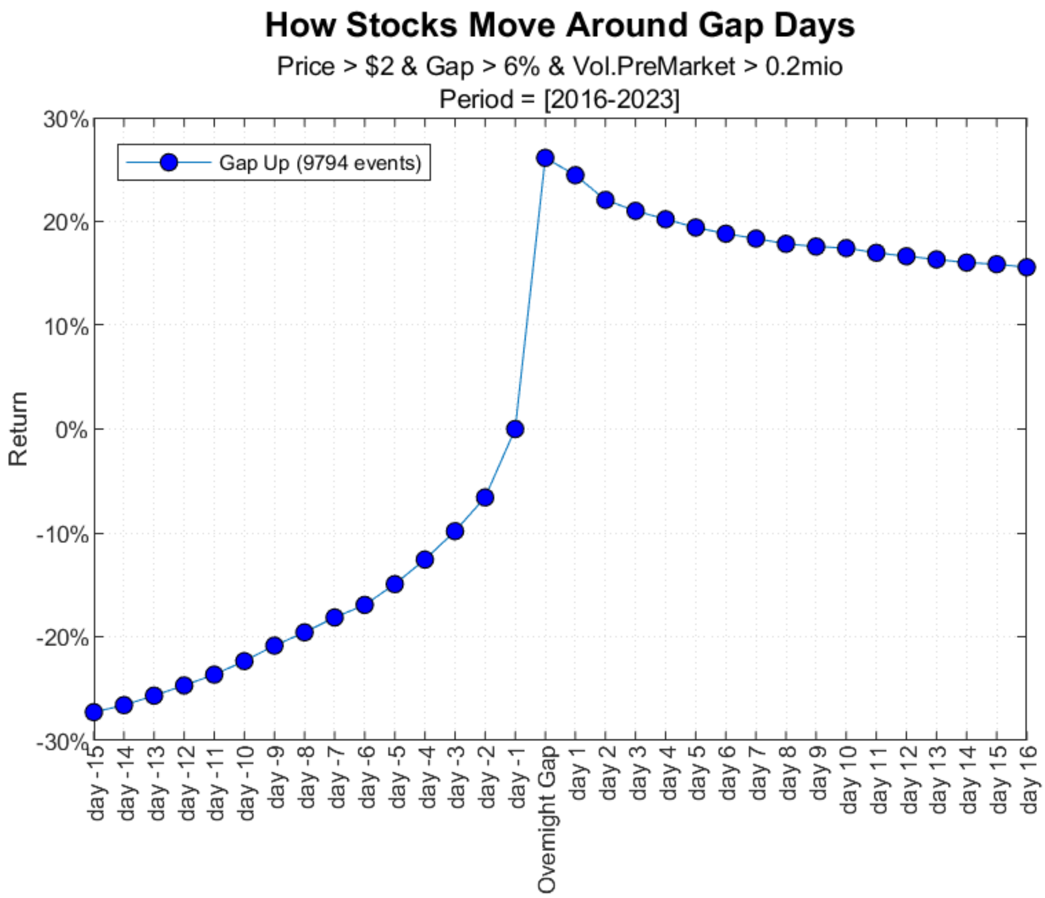


Figure 1: How Stocks Move Around Gap Days. This figure illustrates the behavior of stock prices around gap days, based on an analysis of 9,794 gap events from 2016 to 2023. The x-axis represents the days relative to the gap event, with negative values indicating days before the gap and positive values indicating days after the gap. The y-axis represents the percentage change in stock prices. The pre-gap period (-15 to -1 days) shows a gradual increase in stock prices, suggesting anticipatory buying or positive market sentiment. The chart exhibits an average 28% overnight gap in our dataset, reflecting the immediate market reaction to new information. Following the overnight gap, stock prices typically drift downward gradually. After 16 days, they tend to settle at a price that remains, on average, 15% above the close prior to the overnight gap. This post-gap pattern indicates that prices often overshoot on the gap day, likely due to investors overreacting to new information.

Overnight Gap

The average overnight gap experienced by stocks in our selected dataset is around 25%. This significant rise highlights the market's immediate response to new information, such as earnings announcements or major news releases. The dramatic overnight jump in stock prices reflects the market's rapid adjustment as the new information is swiftly incorporated into stock valuations.

Post-Gap Behavior (+1 to +16 days)

Following the overnight gap, stock prices typically drift downward gradually. After 16 days, they tend to settle at a price that remains, on average, 15% above the close prior to the gap day. This post-gap pattern indicates that prices often overshoot on the gap day, likely due to investors overreacting to new information.

We then examine the profitability of six rules-based quantitative trading strategies applied to all gap events within the 2016-2023 dataset. These strategies are implemented without discretionary influence and are defined as follows:

1. **Open – No Stop**: Enter a long position at 9:30 AM and hold for 30 days without a stop loss.
2. **Open – Stop at 1 ATR**: Enter a long position at 9:30 AM, holding for 30 days with a stop loss set at 1 Average True Range (ATR)[1] from the entry price.
3. **All OR**: Enter at the break of the 5-minute opening range high, with a stop loss placed 1 cent below the low of the first 5-minute candle, holding for 30 days or until the stop is hit.
4. **Pos OR**: Enter at the break of the 5-minute opening range high for stocks with a positive 5-minute opening move, with a stop loss placed 1 cent below the low of the first 5-minute candle, holding for 30 days or until the stop is hit.
5. **Pos OR + Trailing**: Similar to **Pos OR** but with a trailing stop set using a 10-day simple moving average, holding for 30 days or until the stop is hit.
6. **Pos OR + Trailing + 4 Targets**: Similar to **Pos OR + Trailing** but includes four profit targets, selling 25% of shares at each target set at 2R, 4R, 8R, and 10R

[1]The Average True Range (ATR) is a technical analysis indicator used to measure market volatility. It was introduced by Wilder (1978) in his book, *New Concepts in Technical Trading Systems*. The ATR calculates the average range between the highest and lowest prices over a given number of past trading sessions, typically 14 days. This range includes the comparison of the current high to the previous close, the current low to the previous close, and the current high to the current low. The ATR does not indicate price direction but rather the degree of price volatility. High ATR values indicate high volatility, suggesting wider price ranges and potentially greater risk or opportunity for traders. Conversely, low ATR values suggest low market volatility, indicating tighter price ranges.

(where R represents the risk unit, defined as the difference between the entry and the stop loss).

The profitability of each strategy is assessed over a 30-day period, taking into account varying stock volatilities. Profitability is measured in terms of the trade risk unit (R), providing a standardized metric to compare performance across different strategies. For example, if a trade is entered at $100 with a stop placed at $98, the implied risk unit is $2. If after n days the unrealized PnL is $8, it is considered a PnL of 4R ($8/$2). For the **Open − No Stop** strategy, the risk unit is set to 1 ATR.

As exhibited in Figure 2, the strategy of buying all gaps without a stop loss, denoted as **Open − No Stop**, demonstrates a significant negative edge, with cumulative daily losses reaching a minimum of -0.25R after 8 days. This indicates that trading without a stop loss may lead to consistent losses.

The addition of a stop loss, as seen in the **Open − Stop at 1 ATR** strategy, provides a noteworthy but insufficient improvement. This strategy shows a less steep decline from the second day onwards, reaching a minimum of -0.17R after 8 days. This suggests that if a stock shows weakness on the gap day, a trader is better off closing the positions quickly to avoid accumulating further losses in the following days.

Implementing a 5-minute opening range breakout (ORB) entry rule slightly improves the average profit and loss (PnL) profile, yet it remains inadequate. The **All OR** strategy shows a modest enhancement in performance but still fails to yield profitability.

Focusing on stocks that exhibit a positive movement in the first 5 minutes, the **Pos OR** strategy shows further improvement. However, it continues to be unprofitable.

The addition of a trailing stop in the **Pos OR + Trailing** strategy enhances the results slightly, but not sufficiently.

Finally, the introduction of four profit targets, as seen in the **Pos OR + Trailing**

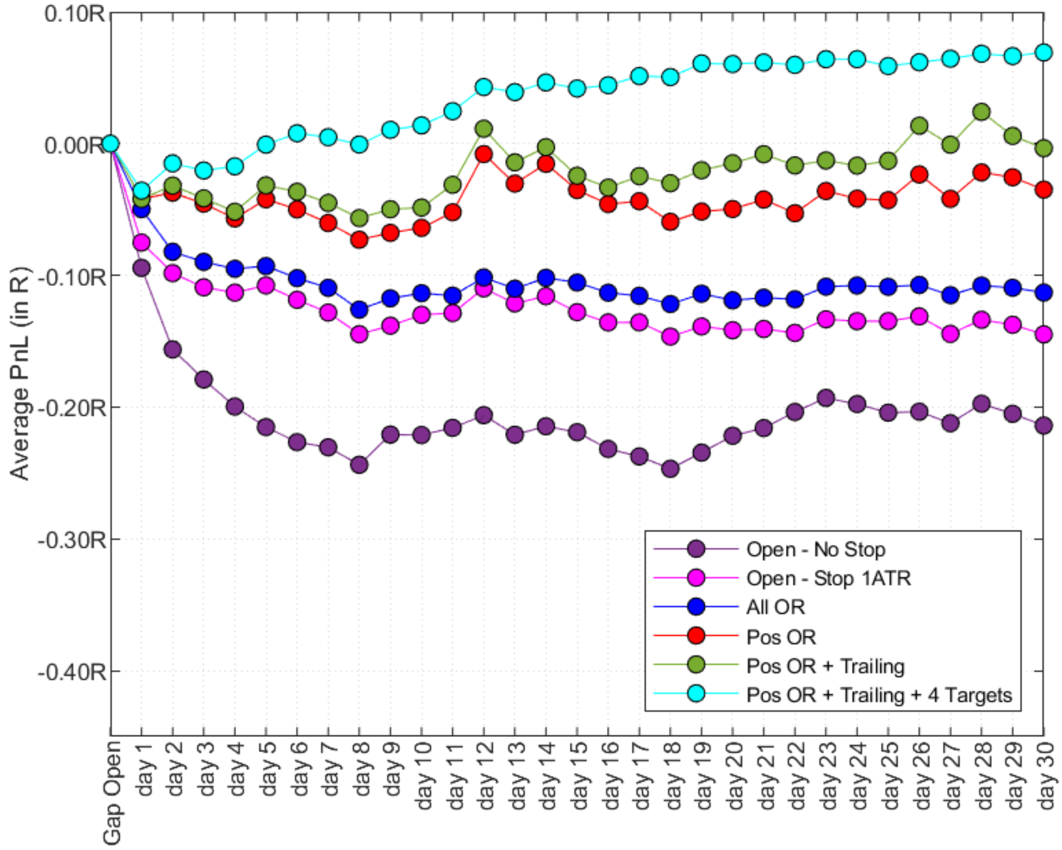


Figure 2: Profitability after a Gap Event. This figure depicts the average cumulative return, measured in risk units (R), for six different trading strategies in the 30 days following a gap event. The study is based on 9,794 gap events that occurred from 2016 to 2023. The strategies range from basic long positions without stop losses to more complex strategies incorporating stop losses, trailing stops, and profit targets, highlighting the relative performance and effectiveness of each strategy.

+ 4 Targets strategy, leads to a noticeable improvement in the average cumulative PnL. This strategy becomes slightly profitable from the tenth day onwards. Despite this improvement, the profitability remains marginal and does not indicate any significant exploitable trading edge using these basic mechanical rules.

Including discretionary intuition in a quantitative backtest

Before concluding that there is no exploitable edge in buying stocks that gap up on catalyst days, we decide to conduct a further test. Although our initial results indicates that most stocks tend to plateau or decline after an initial gap up, we identify a subset of outliers within the dataset that exhibit remarkable performance. This observation prompts us to explore whether a skilled trader, through experience and intuition, could

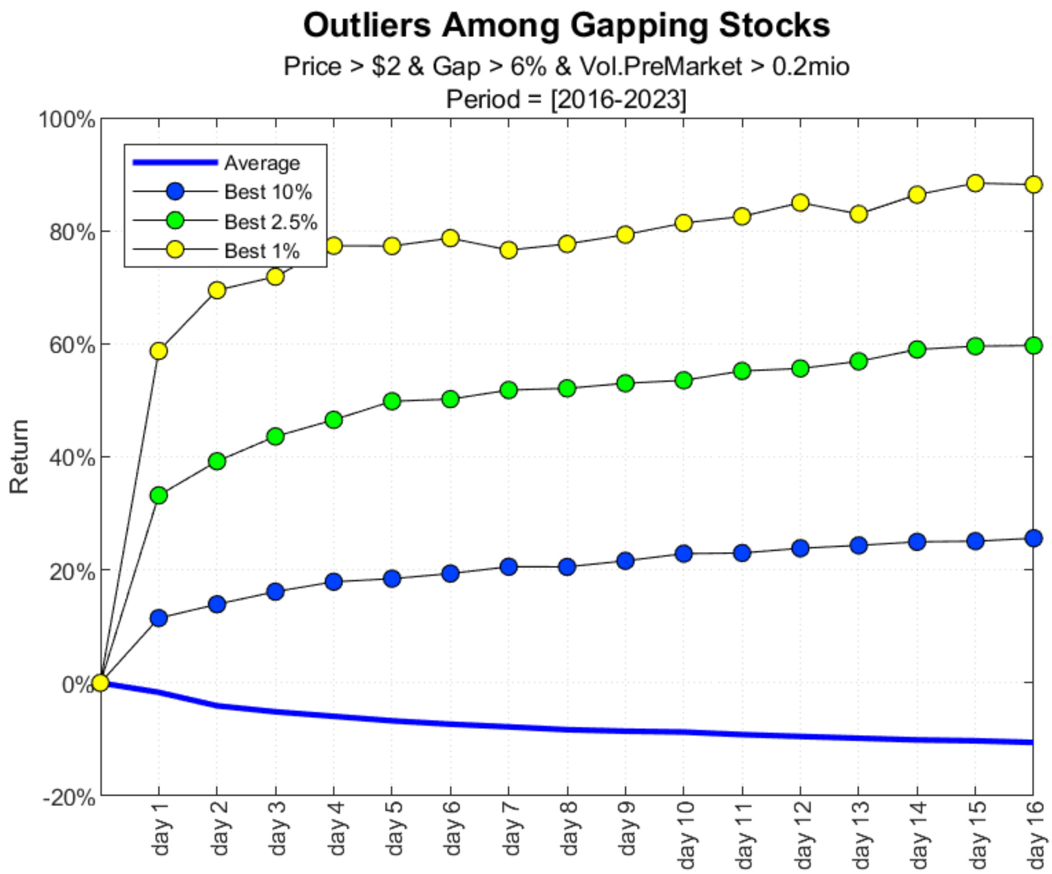


Figure 3: Positive Outliers. This figure illustrates the performance of gapping stocks from the gap day up to 16 days later, analyzing 9,794 gap events from 2016 to 2023. The top 10%, 2.5%, and 1% of stocks show significant gains, with returns reaching up to 85% by day 16 for the top 1% percentile, highlighting the potential for identifying high-performing stocks within the broader dataset.

potentially identify and selectively trade some of these high-performing outliers, thereby unlocking significant profit potential.

As previously discussed, Figure 3 confirms that, on average, stocks tend to move downward in the days following the overnight gap. However, the top-performing stocks show significant and sustained gains. The top 10% of stocks achieve a return of 15% on the gap day, continuing a steady upward trend to reach returns of 22% by day 16. The top 2.5% of stocks demonstrate even more remarkable performance, with returns of 37% on day 1 and a faster upward trajectory, reaching over 60% by day 16. The top 1% of stocks exhibit the most substantial growth, attaining returns of 60% on day 1 and approximately 85% by day 16.

This observation forms the basis for an innovative approach: by leveraging advanced analytical tools and trader intuition, it may be possible to pinpoint these high-performing stocks within the broader dataset. Such a strategy could involve rigorous pre-market analysis, pattern recognition, and leveraging historical performance data to isolate stocks with the highest potential for continued gains post-gap.

Given the experience and internationally recognized trading skills of one of the co-authors, this trader volunteeres to participate as a test subject to evaluate, from a daily chart perspective, all the gaps in the database. Recognizing the potential for bias in such a dual role, rigorous measures are implemented to maintain the integrity of the study.

To ensure the discretionary trader's decisions are not influenced by external biases, the lead author and their team develop a specialized software in Matlab. This unique software anonymizes charts and removes all extraneous information, creating an environment where decision-making is based solely on visual patterns and technical indicators, thereby showcasing our commitment to rigorous and unbiased experimental conditions.

The software removes the following elements:

- Specific dates and times
- Ticker symbols and company names
- Sector and industry classifications
- News events or headlines
- Price levels and volumes

Gaps are randomly selected from the entire database, preventing any calendar bias within the discretionary selection process. This meticulous setup, enabled by custom software, ensures that the discretionary trader's decisions are based solely on visual inspection of the price patterns and moving averages, highlighting our commitment to creating a unique, unbiased experimental environment.

Figure 4: Gap Selection. This figure shows the main interface of the software that allows the discretionary trader to select the most promising gaps. The software displays anonymized charts with user selections for 6-month, 1-year, and 2-year data, shows gap percentages, and allows users to approve, discard and navigate to the next anonymized charts in the dataset in a random order. More details on how the application was used by the trader are shown in a short demo video available here.

The software allows the trader to analyze the two-year daily chart preceding the gap day for all the events within the gap database. The trader's task is to approve or reject each gap based on his intuition and judgment, focusing on whether the prior price action indicated a potential trading opportunity. To maintain the experiment's integrity, no feedback is provided regarding the performance of the approved or rejected charts until the study concludes. The main interface of the software is exhibited in Figure 4. A short video demonstrating the functionalities of the software can be found here[2].

After analyzing the daily charts of all 9,794 gap events in our database, the trader approved 1,721 gaps, approximately 18% of the original dataset.

Before delving into the performance statistics of this subgroup of gaps, it is essential to highlight some of the key factors considered by the discretionary trader during the approval process.

[2]https://youtu.be/t5XqYksepdk

Factors Favored by the Discretionary Trader in the Selection Process

1. **Gaps Following a Neglect Period**: These are favored as they signal renewed interest and potential upward momentum.

2. **Multiweek/Multimonth Range Breakouts**: Preferred due to their indication of a strong breakout with high potential for continued movement.

3. **Gaps Early in the Momentum Cycle**: Early gaps in the momentum cycle are favored over those occurring later.

4. **Avoiding Gaps Following Consecutive Gaps**: Gaps that occur immediately after a gap on the previous day are not favored, as they often suggests potential exhaustion.

By concentrating exclusively on the gaps approved by the discretionary trader, we extend the statistical analysis discussed and illustrated in Figure 2.

For all the approved gaps, we implement a 5-minute Opening Range Breakout (ORB) entry technique, setting the stop at the low of the opening range and trailing the position using a 10-day simple moving average. Additionally, we establish four profit targets, each accounting for 25% of the position, at 2R, 4R, 8R, and 10R.

Figure 5 depicts the performance trajectory of this strategy, termed **Pos OR + Trailing + 4 Targets + Trader**. The average profitability demonstrates a marked improvement, as it increases progressively, reaching a peak at 0.25R, 12 days after the entry day (the gap day). This outcome suggests that the discretionary selection by an experienced technical trader can enhance the profitability of an otherwise unproductive rule-based trading strategy.

Micromanagement in Trading

In practical application, discretionary technical traders use pattern-recognition techniques to identify potential trades from historical daily charts. Additionally, they rely on their

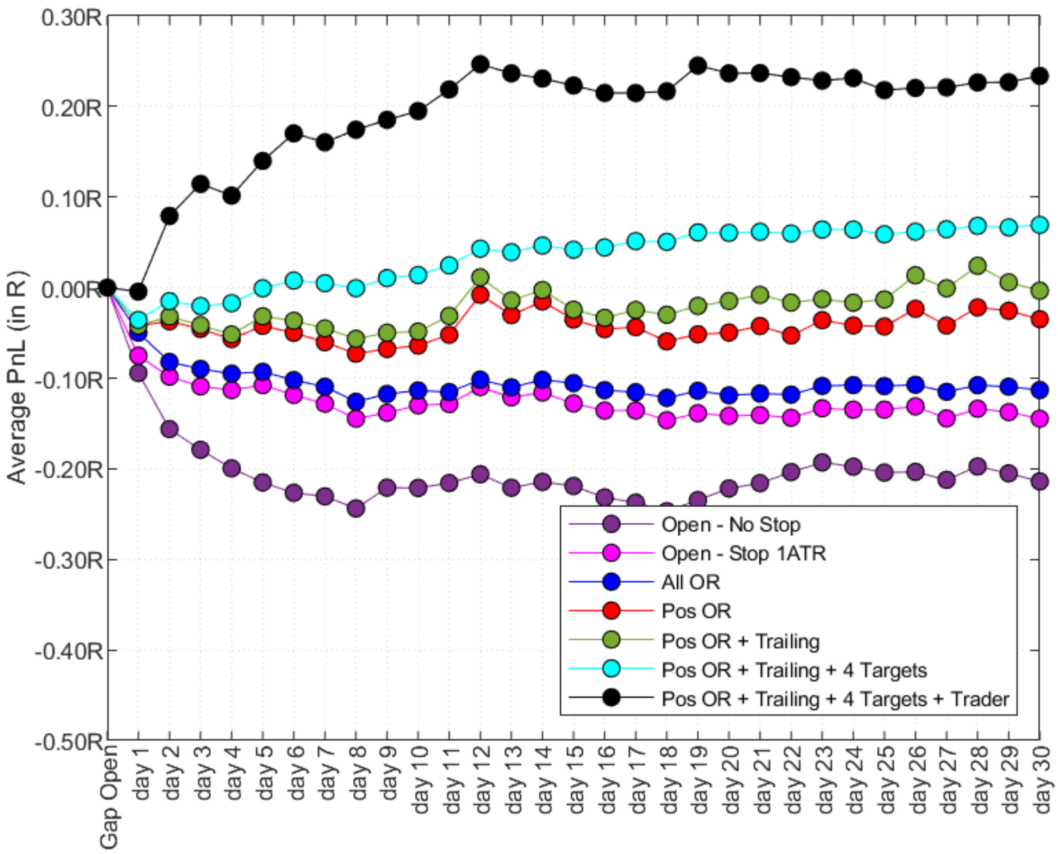


Figure 5: The Role of Discretionary Gap Selection. This figure depicts the average cumulative return, measured in risk units (R), for seven different trading strategies over a series of 30 days, based on an analysis of the 9,794 gap events from 2016 to 2023. The strategies range from basic long positions without stop losses to more complex strategies incorporating stop losses, trailing stops, and profit targets, highlighting the relative performance and effectiveness of each strategy. The first six strategies are applied to a non-discretionary database, while the last one employs the filtered database selected by the trader.

intuition and price-action reading skills on intraday time frames to determine optimal entry prices, stop-loss levels, and profit targets. This amalgamation of techniques and skills epitomizes the micromanagement of identified trading opportunities.

Micromanagement in trading entails the meticulous oversight and fine-tuning of individual trades. Effective micromanagement can augment trading performance by optimizing the risk-reward ratio and mitigating psychological biases. By setting specific entry and exit points, traders can eschew emotional decision-making and adhere to a disciplined strategy. This study investigates whether integrating discretionary trading with structured micromanagement can enhance trading outcomes.

Figure 6: Micromanagement. This figure shows the main interface of the trade management software. The interface displays an intraday chart on the left, highlighting the gap day with designated entry and stop-loss levels, and a daily chart on the right. Users can navigate the intraday chart in 1-minute intervals to accurately determine the entry point and set the stop-loss level. After the position is open, navigation through the daily chart is available in 1-day intervals. The software enables trade execution and provides real-time updates on trade performance (R-multiples) of the open position. It includes functionality to close portions of the trade, divided into four equal parts (25% each). Further details on the application's utility in trade management can be found in this demo video.

To incorporate the micromanagement component employed by discretionary technical traders, we enhance the proprietary software discussed in the previous section. The interface of the new software is exhibited in Figure 6 while a short video with further details can be found here[3].

The enhanced software is designed to enable discretionary traders to identify the optimal entry level, stop-loss, and effectively manage positions for each gap previously validated based on the daily chart. Specifically, the software requires the trader to pinpoint the optimal entry moment on the gap day using intraday price information at a 1-minute frequency. To prevent forward-looking biases, the trader must progress bar by bar until the ideal entry moment is identified. Once the entry point is established, the software

[3]https://youtu.be/b-aBjUk23hQ

mandates that the trader declare the initial stop-loss level. If the trade is not stopped out on the gap day, the trader is permitted to manage the open position by taking partial profits over the subsequent 50 days, with the ability to advance at 1-day intervals. The software allows for a maximum of four partials, each representing a 25% portion of the position, ensuring overall flexibility in trade management. If a position is stopped out before all partials are manually taken, the software calculates and saves the process and populates a new chart in a random order. To maintain an unbiased environment, the software conceals information that could create bias, such as the names of companies, ticker symbols, volume, news, specific prices, dates, and the overall market environment.

Below we provide a short description of the **Factors Favored by the Discretionary Trader in the Micromanagement Process**:

Entry Points

The primary entry strategy focuses on 5-minute opening range breakouts or anticipating such breakouts. Given the propensity for most gaps to be filled (or partially filled), and with only one entry attempt allowed, the trader often exercises patience. If the stock violates the day's lows, the trader would wait for it to potentially reach a previous support area based on the daily timeframe. Forming higher lows after a drop is considered an additional advantage. Although the trader does not have visual representations of Exponential Moving Averages (EMAs) and Volume Weighted Average Price (VWAP), he relies on experience to estimate these levels, and signs of strength around these estimated levels are also favored.

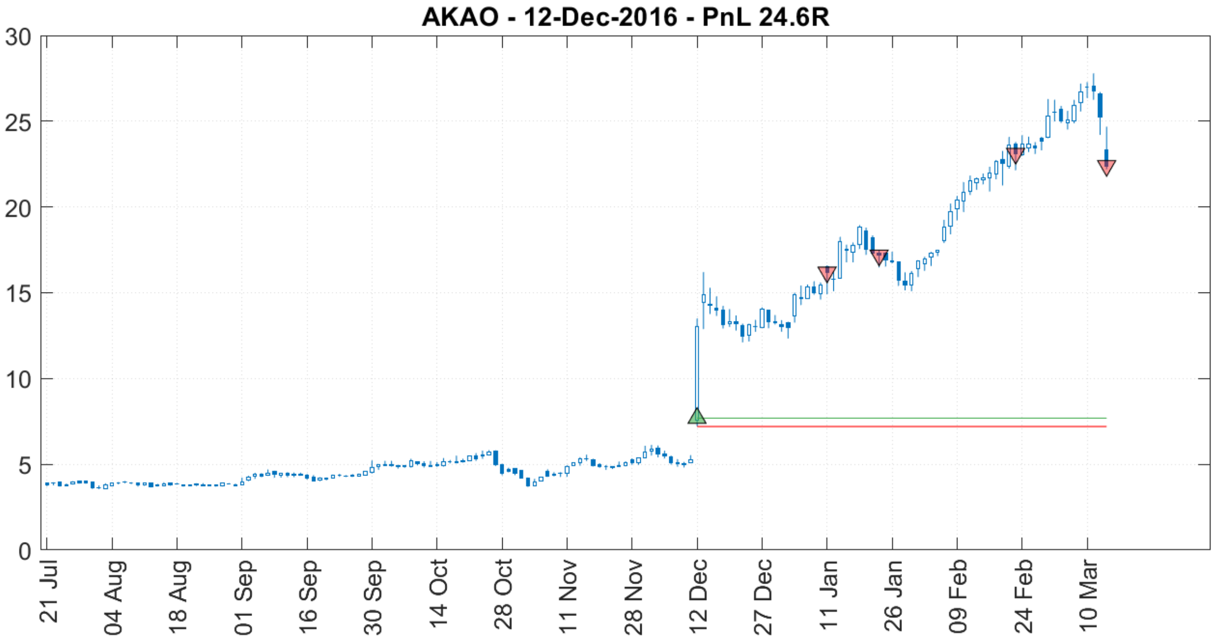
Stop Losses

Stop losses are typically placed just below the low of the day rather than at key support levels. This approach was crucial in limiting potential losses and protecting capital.

Position Management

The position was divided into four parts (25% each), with partial exits planned to secure profits during strong price movements. The trader advances the daily chart by pressing the *+1Day* button, allowing for incremental adjustments. Partial exits are executed in four distinct phases, providing structured opportunities to lock in gains. Subsequent exits are managed by trailing key moving averages. Initial exits are based on trailing the 10-day and 20-day moving averages, with positions exited when a candle closes below these averages. If multiple R (risk multiples) are generated from the entry, and given the program's design limitations on adding positions, the 50-day moving average is also considered for exits. In scenarios where the stock exhibits parabolic movement within a short timeframe, some partials are taken to capture profits efficiently.

Figure 7 illustrates a stock exhibiting a gap up, which was initially validated during the first phase of selection and subsequently micromanaged by the trader. The upper chart represents the daily timeframe spanning approximately four months before the Gap Up event and around three months following the event. It also details the entry and stop-loss levels and partials taken within this period. The price behavior on the daily chart, prior to the event, aligns with the **Factors Favored by the Discretionary Trader in the Selection Process** previously discussed. The intraday price behavior, depicted in the lower chart, shows how the trader identified an entry point and a stop-loss level, adhering to the **Factors Favored by the Discretionary Trader in the Micromanagement Process** discussed earlier. This specific example resulted in a total return of 24.6R after four partial exits, each comprising 25% of the position, over a period of 92 days.



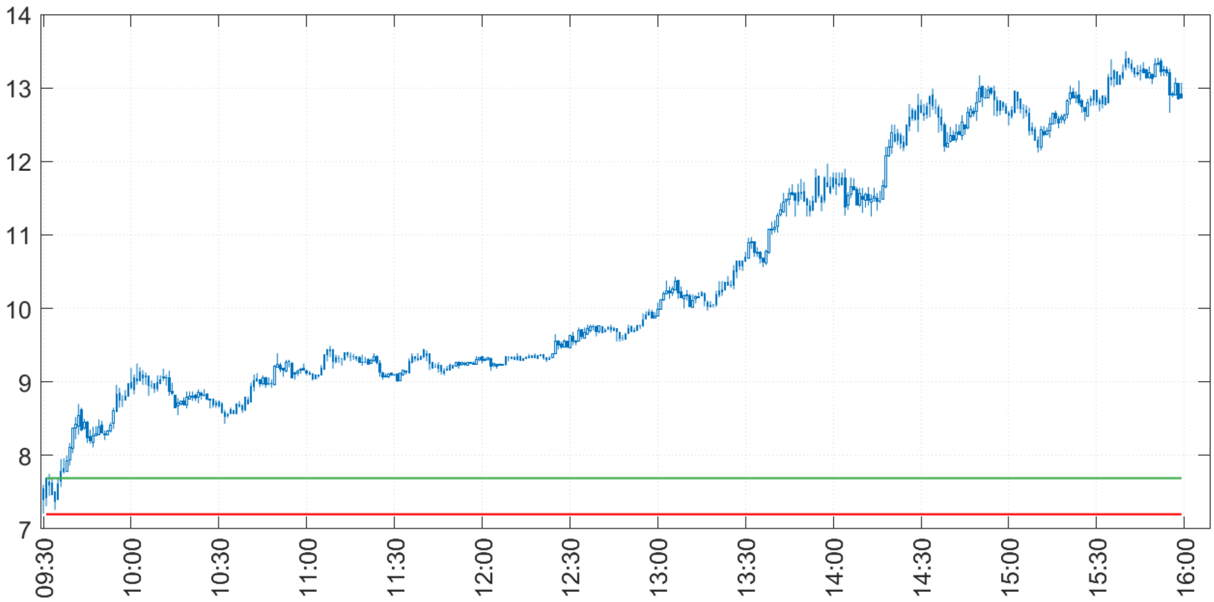


Figure 7: Micromanagement Example. These charts provide an example on how the trader micromanaged the exposure in **AKAO**, a stock that significantly gapped up on December 12, 2016. The upper chart displays the daily price movements for four months before and three months after the gap up, highlighting entry, stop-loss levels, and partial exit points. The lower chart captures the intraday price action on the gap up day, identifying specific entry and stop-loss levels. The discretionary trading strategy, adhering to previously discussed factors, achieved a total return of 24.6R with four partial exits, each representing 25% of the position, over a 92-day period.

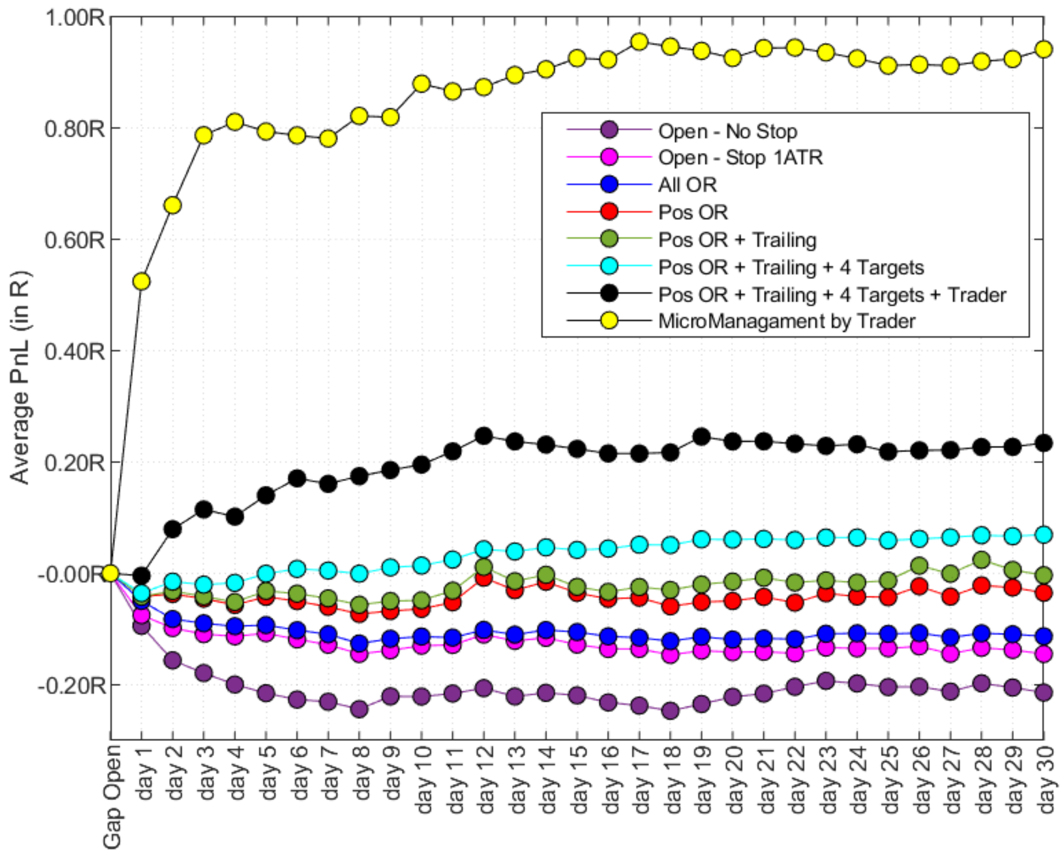


Figure 8: The Role of Micromanagement. This figure depicts the average cumulative return, measured in risk units (R), for eight different trading strategies over a series of 30 days, based on an analysis of the 9,794 gap events from 2016 to 2023. The strategies range from basic long positions without stop losses to more complex strategies incorporating stop losses, trailing stops, and profit targets, highlighting the relative performance and effectiveness of each strategy. The first six strategies are applied to a non-discretionary database, strategy in black include a discretionary selection of gaps based on chart pattern preceding the gap day, while the line with yellow dots also includes the micromanagement of entries, stops and profit targets.

By using the database of all the trades taken and micromanaged by the trader in the bias-free environment, we update Figure 5 and plot the average cumulative PnL in R-multiples. As shown in Figure 8, there is a significant improvement in the average profitability. The average profitability on the gap day increases to 0.55R, reaching a local maximum of 0.80R on day 4. After 3 days of a shallow pullback, profitability starts increasing again, but at a slower rate. This is likely because the trader allows the full position to run for the first three days, then reduces risk by taking partial profits and letting a quarter position trail on a longer moving average.

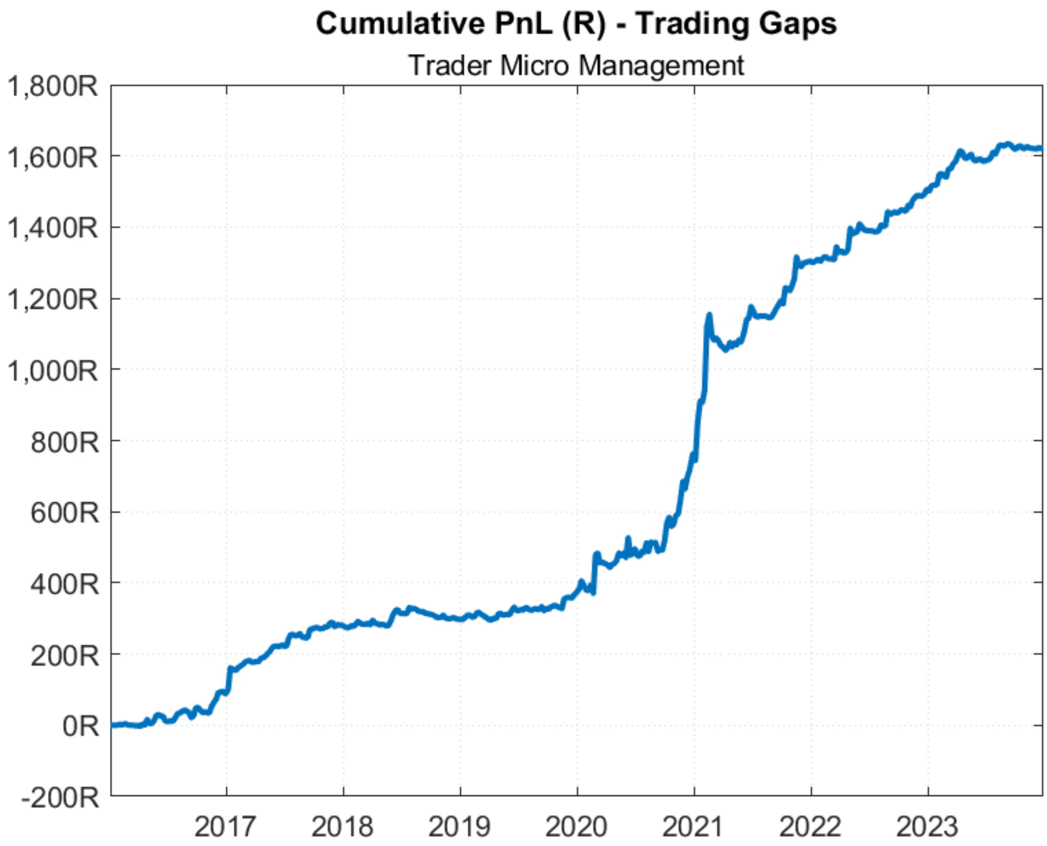


Figure 9: Cumulative PnL in R. This figure exhibits the cumulative Profit&Loss (PnL) in R of a portfolio exposed to all the trades micromanaged by the trader using a specialized, unbiased environment built in Matlab. The data is sourced from CRSP, IQFeed, and Polygon, covering the period from January 2016 to December 2023.

All the trades simulated in the bias-free environment are analyzed from a cumulative chronological perspective; we reorder chronologically all the gaps taken and micromanaged by the trader and plot in Figure 9 the cumulative PnL in R collected from 2016 to 2023. We notice a trajectory characterized by sharp upward movements, which tend to correspond to strong bullish market periods. Overall, this hypothetical portfolio accumulates more than 1,600R in seven years without experiencing long periods of drawdown.

As suggested by the trader, these trades are usually sized so that if a stop loss is hit, the resulting loss at the portfolio level equates to 0.25%. We thus transform the cumulative PnL time-series into a monetary time-series, assuming an initial equity of $100,000 and a risk budget per trade of 0.25%. The trajectory of the simulated account is exhibited in Figure 10. A $100,000 portfolio grows to more than $4,000,000, yielding a total return

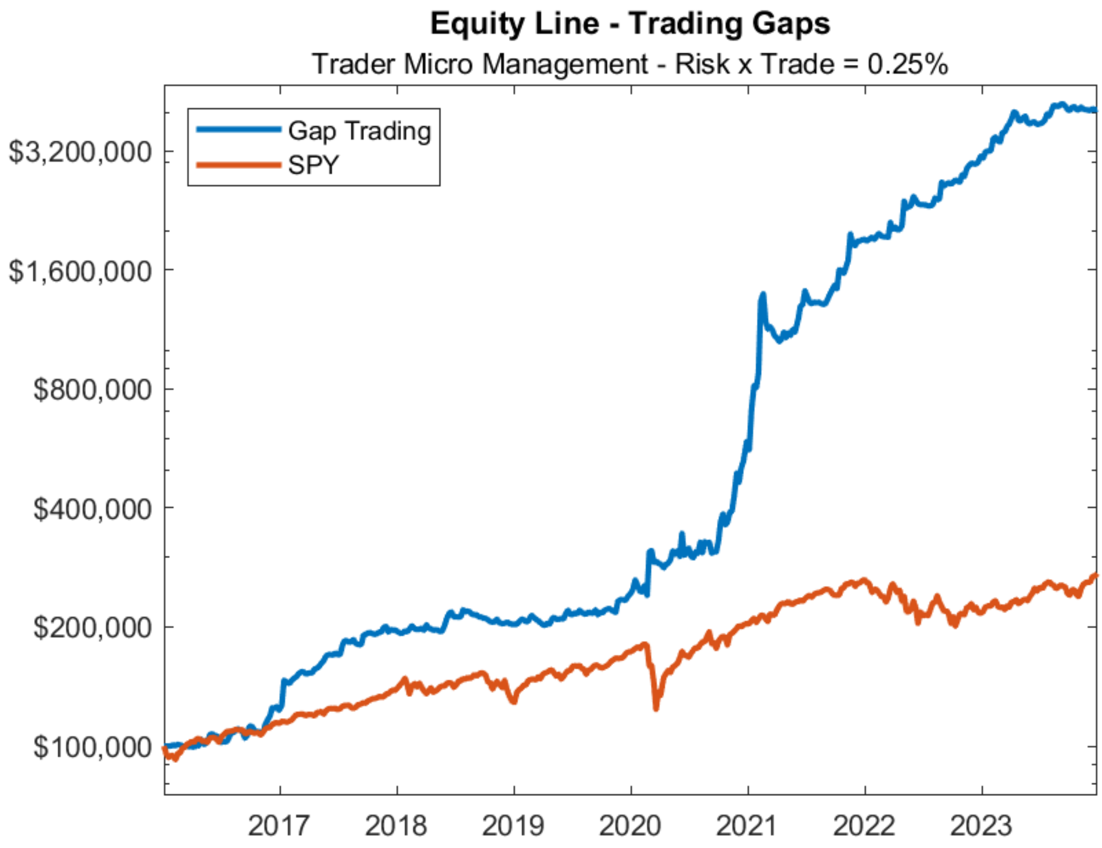


Figure 10: Equity Line. This figure exhibits the equity evolution of a $100,000 investment in a portfolio exposed to all the trades micromanaged by the trader using a specialized, unbiased environment built in Matlab. Each trade is sized such that if a stop-loss is hit, the overall portfolio loses 0.25% of its equity. A transaction cost of $0.01 per share is included in each execution. For comparison, the trajectory of an investment of the same size in SPY, the most liquid ETF tracking the S&P 500, is also included in the chart. The data is sourced from CRSP, IQFeed, and Polygon, covering the period from January 2016 to December 2023.

of 3,968% in 8 years.

Table 1 provides a detailed overview of the trading strategy's performance, showcasing its remarkable effectiveness and resilience. Over the study period, the strategy achieves a total return of 3,968%, with an impressive compounded annual growth rate (CAGR) of 59.1%. The volatility, measured at 29.9%, indicates a moderate-to-high level of risk, while a Sharpe Ratio of 1.70 highlights strong risk-adjusted returns.

Daily hit rates reveal that the strategy achieves positive returns 50% of the time, reflecting a balanced probability of daily gains and losses. On a monthly basis, the strategy

Table 1: Performance Statistics. This table presents key summary statistics for a portfolio constructed using all the trades micromanaged by the trader within a specialized, unbiased environment built in Matlab. Each trade is sized such that if a stop-loss is hit, the overall portfolio loses 0.25% of the portfolio equity. The CAGR represents the Compounded Annual Growth Rate for the strategy. A transaction cost of $0.01 per share is included in each execution. The data is sourced from CRSP, IQFeed, and Polygon, covering the period from January 2016 to December 2023.

Total Return	3,968%	**Worst Day Return**	-14.4%
CAGR	59.1%	**Worst Day Date**	23-Feb-2021
Volatility	29.9%	**Best Day Return**	22.1%
Sharpe Ratio	1.7	**Best Day Date**	07-Jan-2021
Hit Ratio (daily)	50%	**Trades**	1,580
Hit Ratio (monthly)	69%	**Average PnL**	1.03R
Hit Ratio (yearly)	100%	**Average Gain**	10.10R
Maximum Drawdown	35%	**Average Loss**	-1.02R
Skewness (daily)	3.01	**Trade Win Rate**	18%

records positive returns 69% of the time, suggesting a consistent pattern of monthly profitability. The strategy's yearly hit rate stands at 100%, indicating it delivers positive annual returns every year, exemplifying long-term performance stability.

The strategy encounters a maximum drawdown of 35% in 2021, reflecting the largest peak-to-trough decline. A skewness of 3.01 points to a return distribution with a tendency for occasional large gains. The worst single-day return is -14.4%, occurring on February 23, 2021, while the best single-day gain of 22.1% is recorded on January 7, 2021.

In terms of trading activity, the strategy executes 1,580 trades over the period, illustrating its active approach. The average PnL per trade is 1.03R, indicating that on average, trades slightly exceeds the initial risk taken. Winning trades have an average gain of 10.10R, showcasing significant profitability, whereas losing trades have an average loss of -1.02 R, reflecting effective loss control. The trade hit rate, at 18%, indicates that approximately one in five trades are winners, underscoring the strategy's reliance on substantial gains from winning trades to drive overall profitability.

This detailed performance analysis highlights the strategy's ability to navigate and cap-

Table 2: Monthly Returns. This table presents the monthly returns (in percentage terms) for a portfolio constructed using all the trades micromanaged by the Trader within a specialized, unbiased environment built in Matlab. Each trade is sized such that if a stop-loss is hit, the overall portfolio loses 0.25% of the portfolio equity. A transaction cost of $0.01 per share is included in each execution. The data is sourced from CRSP, IQFeed, and Polygon, covering the period from January 2016 to December 2023.

Year	**Jan.**	**Feb.**	**Mar.**	**Apr.**	**May**	**Jun.**	**Jul.**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**	**Yearly**
2016	0.0	0.0	0.0	2.6	-3.3	-1.5	2.1	-1.2	5.0	-1.5	8.8	2.7	**14**
2017	17.9	5.6	0.2	2.8	7.3	1.0	8.0	-1.2	5.6	0.9	32.7	2.9	**116**
2018	0.3	5.0	-0.3	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-1.0	**4**
2019	0.4	-1.2	-2.3	3.6	-0.5	0.3	-0.2	0.0	0.0	0.0	0.0	0.0	**0**
2020	-0.8	-1.0	-0.7	-1.5	-0.6	-1.3	-4.9	1.1	-4.6	-1.2	26.9	23.9	**34**
2021	19.4	74.0	-6.0	1.6	3.2	13.8	0.4	-2.7	11.6	10.4	18.4	2.0	**239**
2022	0.2	1.6	5.7	9.1	7.9	-3.1	1.1	11.2	1.7	3.3	8.0	4.8	**64**
2023	7.4	0.6	14.5	-2.7	-2.7	6.5	23.4	5.5	-2.9	0.5	0.3	0.0	**59**

italize on market conditions effectively, combining high returns with controlled risks to achieve consistent long-term growth.

Table 2 demonstrates the trading strategy's strong adaptability and resilience from 2016 to 2023. Notably, in 2017 it achieves a remarkable 116% return, while in 2021 the portfolio increases by 239%, underscoring exceptional performance during volatile periods. February 2021 marks the highest single-month return at 44.5%, followed by the worst monthly loss in March 2021 at -6%. There is a clear positive asymmetry in monthly returns, a statistical property typically found among trend-following strategies.

During the pandemic years, the strategy exhibits exceptional adaptation, achieving its highest returns. In 2022, it balanced high returns with reduced volatility, ending with a 64% annual return. Additionally, the 2023 performance appears remarkable with strong gains in January, March, and July.

Overall, the strategy's consistent high returns, effective market timing, and robust performance during volatile periods highlight its efficacy and resilience across various market conditions.

5 Conclusion

This study presents compelling evidence on the significant benefits of integrating discretionary technical trading into automated strategies, particularly for stocks experiencing substantial overnight gaps. By rigorously analyzing 9,794 gap events from 2016 to 2023, we demonstrate that the intuition of experienced traders can enhance the profitability of trading strategies.

Our key findings reveal that when stocks gap up, the application of discretionary trading decisions, implemented in this investigation using specialized anonymizing software, leads to substantial improvements in trading performance. The discretionary trader's selection of approximately 18 percent of the gap events results in higher average trade profitability compared to purely mechanical approaches. This underscores the critical role of intuition and experience in identifying and capitalizing on market opportunities that automated systems might overlook.

The ability of the discretionary trader to recognize favorable patterns, such as early gaps in momentum cycles and multi-week or multi-month range breakouts, plays a pivotal role in improving trade selection. Additionally, the structured micromanagement techniques applied, including precise entry points, stop losses, and profit targets, further enhances trade outcomes by optimizing risk-reward ratios and ensuring disciplined trade execution.

The use of specialized software to anonymize charts and eliminate extraneous information ensures an unbiased evaluation of the trader's decisions. This innovative approach isolates the effects of bias from external factors and prevents any forward-looking bias, allowing the incorporation of the trader's discretionary intuition into a quantitative empirical investigation. The cumulative PnL achieved on the discretionarily selected and traded gaps shows a significant growth trajectory, with the hypothetical portfolio achieving a total return of nearly 4,000% over eight years. This performance demonstrates the potent combination of human intuition and systematic trading rules.

In conclusion, this study bridges the gap between discretionary and algorithmic trading, providing empirical evidence of the substantial value that trader intuition may add. By leveraging the unique strengths of experienced traders, systematic strategies can achieve superior performance, greater consistency, and enhanced risk management. This hybrid approach offers valuable insights for individual traders and institutional investors alike, presenting a promising pathway for future research and practical application in the ever-evolving landscape of financial markets.

Author Biography

Carlo Zarattini, originally from Italy, currently resides in Lugano, Switzerland. He holds a degree in mathematics from Padova and a dual master's in quantitative finance from Imperial College London and USI Lugano. Formerly a quantitative analyst at BlackRock, Carlo developed volatility and trend-following trading strategies. He later founded Concretum Group, a data-driven quant boutique that supports sophisticated investors and institutional clients in conducting quantitative investment research and uncovering trading opportunities across various markets and timeframes. Additionally, he established R-Candles.com, the first online backtesting platform for discretionary technical traders. Carlo actively publishes research on SSRN.com on intraday trading strategies, momentum trading, and trend-following. One of his papers received an award at the Quantpedia Awards 2024.

Marios Stamatoudis is a distinguished trader with years of experience specializing in asymmetric opportunities through momentum strategies in U.S. stocks and ETFs. At the age of 26, he earned recognition as a top performer in the 2023 United States Investing Championship, becoming the first Greek to achieve this distinction. His achievements have garnered accolades from the investment community and recognition from leading industry figures and financial publications. Beyond trading, Stamatoudis is actively engaged in research, continually advancing investment methodologies while enhancing his own expertise and knowledge.

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