Pair Trading Using ESABO Co-Movement Analysis

Chinmay Kalvade

Under the supervision of

Dr. Jens Christian Claussen

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School of Computer Science

College of Engineering and Physical Sciences

University of Birmingham

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Declarations

I certify that this project is my original work. Code development was assisted by `ChatGPT 5.0, Gemini 2.5 Pro` and debugging by `Gemini 2.5 Pro`. The report structure and initial drafts are my original work, the proofreading was assisted by `ChatGPT 5.0` for clarity and consistency. All outputs have been reviewed and edited to accurately reflect my work.

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Abstract

Pair trading is a market-neutral strategy that exploits temporary anomaly in the prices of correlated assets, traditionally betting on their convergence. Conventional approaches rely on cointegration. When two or more non-stationary time-series maintain a long-term equilibrium, they are considered to be cointegrated. Empirical evidence suggests cointegrated series are unreliable for stock pairs due to weak or unstable equilibrium, leading to inflated theoretical Sharpe ratios not observed in practice.

This thesis proposes a novel adaptation of ESABO (Entropy Shifts of Abundance Vectors under Boolean Operations), originally developed for detecting microbial interactions, modifying it to identify co-moving stock pairs based on Boolean analysis of binarized equity close prices over time. By thresholding returns into binary states and computing entropy shifts under Boolean operations, ESABO detects equity pairs prone to synergistic co-movements more robustly than cointegration. The proposed method aims to introduce co-movement as a computationally light, robust trade signal to trade equity pairs. This report presents ESABO benchmark tests against standard cointegration methods on S&P 500 stocks from 2019-2025 and demonstrates the strengths and weaknesses of each method. Multiple trade applications including mean reversion, momentum and volatility-based approaches are tested to analyze real-world viability of the method.

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1 Introduction

Statistical arbitrage refers to a class of quantitative trading strategies that seek to profit from temporary anomalies between related financial instruments [17]. A classic example is pair trading, which involves identifying two stocks that historically move in tandem and taking offsetting long/short positions when they diverge, betting on their eventual convergence [14]. In a pair trade, one buys the relatively underperforming stock (goes long) and sells the overperformer (goes short), expecting the spread to "mean-revert" to its typical level [24]. This strategy is market-neutral, it does not depend on the overall market direction since gains on one position can offset losses on the other [23]. In intuitive terms, imagine two companies competing in the same industry: their revenues and stock prices often move together. If one stock temporarily jumps or falls out of sync, pairs traders anticipate it will eventually "catch up" to the other, yielding profit in the process. Indeed, practitioners have long noted that pairs of highly correlated assets often return to their historical correlation after short-lived deviations [23, 33].

Pair trading has a rich history dating back to the 1980s. It was pioneered by a quantitative team at Morgan Stanley led by Nunzio Tartaglia and remained a closely guarded secret of professional traders for years [7, 14]. Academic study followed this practical success. In a landmark empirical study, Gatev et. Al. (2006) tested a simple pairs trading rule on U.S. stocks from 1962 to 2002 and reported compelling results: on average the strategy yielded excess returns of roughly +11-12% per year for long-short, self-financing portfolios of matched stock pairs [8, 39]. These profits were robust even after accounting for plausible transaction costs, suggesting that temporary mispricing between close substitutes can be exploited for gain [4, 8]. Such findings helped cement pairs trading as a paradigmatic example of statistical arbitrage [17]. Importantly, this approach is statistical, it relies on historical patterns and probabilistic models rather than guaranteed arbitrage and hence it requires rigorous methods to find and trade the "right" pairs [17].

Over time, practitioners and researchers have developed more systematic methods for selecting and trading pairs. A core idea is to ensure that a chosen pair has a stable long-run relationship [17]. In econometric terms, it is referred as cointegration between the two price series [40]. Two non-stationary price series are cointegrated if some fixed linear combination of them is stationary, meaning they share a long-term equilibrium [40]. Equivalently, if we form a "spread" (e.g. a linear combination of the stock prices), cointegration implies that this spread tends to revert to a constant mean and variance over time. Thus, any divergence in the spread can be interpreted as a temporary anomaly, precisely the condition for pairs trading. In practice, traders typically screen for highly correlated stock pairs and then perform statistical tests (such as the Engle-Granger or Johansen cointegration tests) to confirm that their spread is mean-reverting [40, 25]. When a cointegrated pair drifts apart beyond a threshold (often defined in terms of standard deviations of the spread), the trader (or trade algorithm) opens a long/short position expecting re-convergence; when the spread returns to normal, the positions are closed [25]. This cointegration based strategy is widely used because it formalizes the notion of mean-reversion and helps avoid false signals from spurious correlations [25]. Other common techniques include distance based methods (matching stocks with historically similar price paths) and methods borrowed from time-series analysis (e.g. Ornstein-Uhlenbeck models for spreads) [17, 2]. Regardless of the approach, the goal remains the same: exploit temporary deviations in related assets while remaining hedged to broad market moves [14].

A pivotal metric for evaluating a trading algorithm's efficacy is the Sharpe ratio, a measure of risk-adjusted return. It quantifies the return generated by a strategy for each unit of risk taken, making it an essential tool for comparing strategies with different risk profiles [19]. Its importance is underscored by the observation that while a strategy might produce high absolute returns, it may also be highly volatile, a characteristic that a high Sharpe ratio would correct for. For example, academic studies on pairs trading often report Sharpe ratios in the range of 0.8 to 1.5, which can be taken as a benchmark for a successful strategy [4, 15]. This metric also highlights the unreliability of traditional methods: a key critique of cointegration is that a truly cointegrated pair would, in theory, generate an unrealistically high Sharpe ratio greater than 10, a value that is simply "too good to be true" and never observed in practice [5, 40].

While cointegration and correlation work with price values, other fields have developed analogous techniques for detecting associations in binary presence/absence data. In microbial ecology, for example, researchers study co-occurrence patterns of species across many environmental samples to infer ecological interactions. Claussen et al. (2017) introduced a novel method called Entropy Shifts of Abundance Vectors under Boolean Operations (ESABO) to analyze such data [3]. ESABO starts from a set of binary abundance vectors: for each microbial species i, we record a 1/0 in each sample indicating whether species i is present (above some abundance threshold) or absent. For any two species i and j, ESABO applies a logical operation (such as AND, OR etc.) to their binary vectors across all samples, yielding a combined vector. It then computes the Shannon entropy of this combined vector and compares it (via a z-score) to the entropy expected under a null model (randomly shuffled occurrences) [3].

Intuitively, this measures how much "information" is gained or lost by the co-occurrence pattern of the two species beyond random chance. A high positive entropy shift (compared to null) might indicate that the two species jointly co-occur more often than expected (suggesting a synergistic or mutualistic interaction), while a large negative shift suggests they rarely overlap (competitive exclusion) [3].

There is a clear conceptual analogy between ecological co-occurrence patterns and financial co-movements [3]. In ecology, two species are said to co-occur if they are found together in the same sample more often than random expectation, often interpreted as a sign of positive association (e.g. mutualism or similar habitat preference) [35]. Conversely, species that infrequently co-occur may compete for resources. In finance, we might think of two stocks "co-occurring" when they move in the same direction (both up or both down) or otherwise exhibit correlated behaviour. In fact, recent studies have explicitly connected co-occurrence concepts to markets: for example, Tang et al. (2022) showed that firms appearing together in news articles (a form of co-occurrence in media) tend to have higher stock return correlations and greater news co-occurrence predicts higher future return correlations. This demonstrates that "co-occurrence" in one sense (co-mention in news) maps to co-movement in returns, reinforcing the idea that pairs or groups of companies sharing information often show synchronized price behaviour. More generally, stocks that share economic characteristics (same industry, supply chain links, or exposure to common factors) tend to exhibit co-movement in prices. For example, index-tracking securities or sector peers often rise and fall together, much like species sharing an ecological niche [33]. This is analogous to positive co-occurrence in ecology. One could also conceive of negative co-occurrence: two competing firms might alternately capture market share (one goes up while the other goes down), akin to competitive exclusion of species. In short, the patterns that ESABO was designed to detect among binary species' data have financial analogues.

These parallels suggest a rationale for adapting ESABO to financial time series. Although stock prices are continuous rather than binary, we can binarize aspects of their behaviour in order to use similar tools. For instance, one could define for each stock a binary time series indicating when its return is positive (presence) versus negative (absence), or whether it is above or below some moving threshold [31]. Then pairs of stocks yield two binary vectors (of 1s and 0s) across trading days. Applying a Boolean AND (or other operation) to such a pair effectively isolates days when both stocks move up together. Computing the entropy shift of this combined vector (relative to random reshuffling) would measure how unexpectedly coordinated their movements are. In other words, ESABO would quantify the information content of their joint up/down patterns, highlighting pairs that move in concert (potentially positive "interaction" in the stock sense) versus those that avoid moving together. Adapted this way, ESABO can capture aspects of stock co-movement that go beyond linear correlation or cointegration. Traditional measures (Pearson correlation, etc.) assume a linear relationship in value or return space; cointegration assumes a linear equilibrium in price levels. By contrast, the ESABO approach is inherently non-linear and non-parametric: it looks at the pattern of co-occurrence events and uses information entropy to summarize it [3]. It also naturally handles cases where co-movement is occasional or state-dependent (e.g., the stocks move together only under certain market regimes), since it focuses on presence/absence patterns rather than requiring continuous joint variation [3]. In principle, then, ESABO might reveal pairs whose correlation structure is subtle or masked by noise, but whose joint behaviour remains informative in the entropy sense.

The motivation for this thesis is to explore precisely this novel cross-disciplinary idea: using ESABO to identify stock pairs for trading. The core research questions include:

1. Can ESABO co-occurrence scores be used to select pairs of stocks with statistically significant co-movement?

2. Do such ESABO-identified pairs exhibit spreads suitable for pairs trading?

3. How does an ESABO-based strategy compare to classic methods (correlation screening, cointegration tests) in terms of profitability and robustness?

The innovation of this approach lies in detecting a novel type of tradable signal with ability to generate profits reliably while remaining computationally light, ideally benefitting high frequency trading systems executing several thousand intraday trades [19]. If successful, it would provide a fresh, data-driven way to discover trading signals without relying solely on linear econometrics [33]. In practical terms, this thesis will develop a financial ESABO pipeline: transforming price or return series into binary occurrence vectors, computing ESABO scores for many stock pairs, and evaluating the resulting signals via back-testing [2].

2 Literature Survey

The literature on pairs trading reveals a field that, while founded on a successful historical strategy, is in a state of continuous evolution. The seminal work of Gatev, Goetzmann, and Rouwenhorst (2006) established the profitability of a simple, distance-based pairs trading rule [8]. Subsequent research, however, has increasingly documented a decline in the strategy's profitability over time [4]. This attenuation of profits is widely attributed to the increasing prevalence of algorithmic arbitrage, which has led to greater market efficiency and the rapid exploitation of transient mispricing, thereby reducing the duration and magnitude of tradable anomalies [17]. This trend has motivated a search for more sophisticated and robust pair-selection methods [4, 17].

2.1 Traditional Arbitrage

While pairs trading was historically lucrative, a significant body of recent literature documents a decline in its profitability over time [4]. A pivotal study by [4] found that the strategy's profitability had peaked in the 1970s and 1980s and was in a state of consistent decline. They concluded that the strategy documented by [7] was largely unprofitable after 2002 when transaction costs were factored into the analysis [7]. This decline in returns highlights the need for a more rigorous and reliable framework for identifying tradable opportunities [4].

The critique of traditional pairs trading extends beyond mere empirical observation to a more fundamental theoretical challenge of the cointegration paradigm itself. Cointegration is an econometric property of time series that indicates a long-term, stable equilibrium relationship between two or more non-stationary price series [40]. In theory, this mean-reverting property of the spread is precisely the condition required for a profitable pairs trade [2, 17]. However, as [5] contend, true cointegration would imply statistical arbitrage opportunities that are "simply too large to be consistent with the notion that markets are relatively efficient". Their analysis demonstrates that under the assumption of true cointegration, a single pairs trade could generate an annualized Sharpe ratio greater than 10, a figure that is orders of magnitude higher than what is observed empirically in real markets [5]. The fact that observed Sharpe ratios for cointegration-based strategies typically hover in the range of 0.8 to 1.5 demonstrates a clear gap between the econometric theory and market reality [4, 17]. The unavoidable conclusion is that what traditional econometric tests identify as "cointegration" among stock prices is, more often than not, a spurious or temporary statistical signal that does not represent a true, long-run equilibrium [11][40]. This theoretical crisis motivates the search for alternative, non-econometric methods that can identify more robust forms of co-movement [17].

2.2 Alternative Pair-Selection

In response to the limitations of traditional frameworks, a new wave of research has emerged, focusing on non-linear and data-driven methods for identifying co-moving assets [17].

Copulas

One prominent alternative to linear cointegration is the use of copula models [38, 12]. These models are designed to capture the complex, non-linear dependency structure between two or more random variables, independent of their individual marginal distributions [38]. Copulas are particularly adept at modelling "tail dependence," which is the tendency for assets to move together during extreme market events, a relationship that is often missed by linear correlation [12, 38]. By separating the modelling of individual asset returns from their joint dependency structure, copulas can provide a more nuanced and accurate picture of co-movement [12, 38]. For example, studies have shown that dynamic copula models, which account for changing dependencies over time, can yield more robust results than static copula models [38]. However, this advanced statistical approach comes with significant challenges, including high computational cost and mathematical complexity in fitting these models, which can require a minimum of 70 core processors for real-time analysis in large asset universes [28].

Machine Learning and Reinforcement Learning

The field of pairs trading has also witnessed the rapid adoption of computational intelligence techniques [2, 19, 21]. Machine learning (ML) has been applied to various stages of the strategy, from pair selection to optimizing trading rules [2, 17]. More recently, deep reinforcement learning (DRL) has shown promising results in optimizing trading actions in a pairs trading framework [19, 27, 36]. DRL agents are trained to take long, short, or neutral positions based on a spread's state, learning to maximize cumulative profits over time [19]. Some studies show that DRL-based methods can outperform traditional methods, with one analysis of cryptocurrency pairs trading finding DRL-based profits ranging from 9.94% to 31.53% annualized, compared to 8.33% for the traditional method [36]. These methods are highly powerful but are often seen as "black boxes," making it difficult to interpret why a specific trade was selected or how the model captures a co-movement signal [26].

The ESABO method's position in this evolving landscape is unique. It is neither a traditional econometric model like cointegration nor a computationally intensive, black-box ML model [3]. Instead, it offers a non-parametric, information-theoretic approach that is both conceptually simple and computationally light [3]. ESABO can be seen as a bridge between the classic frameworks and the modern ML-driven approaches, offering some of the benefits of non-linear dependence modelling (like copulas) without the extreme complexity or computational cost [3]. This makes it a highly practical and novel tool for statistical arbitrage [3]. To illustrate the unique positioning of these methodologies, a comparative analysis is presented in Table 2.2, summarizing their core principles, strengths, and weaknesses.

Methodology	**Underlying Principle**	**Key Assumptions**	**Primary Strength**	**Primary Weakness**
Distance	Normalized Price Proximity	Non-parametric, no statistical basis [11, 40]	Simplicity, ease of implementation [40]	Lacks a rigorous statistical foundation [40]
Cointegration	Stationary Spread	Linear long-term equilibrium [40]	Formal econometric framework [40]	Prone to spurious signals, unrealistic theoretical returns [5, 40]
Copula	Joint Dependence Structure	Separates marginals and joint distributions [12, 38]	Captures non-linear dependencies and tail-risk [12, 38]	High computational cost and complexity [28]
ESABO	Boolean Co-occurrence	Assumes binarization is informative	Computationally light, non-parametric, robust	Information loss due to binarization

Table 2.1: A Comparative Analysis of Pairs Trading Methodologies

2.3 Risk Management

A sophisticated pairs trading strategy is not defined by a single pair-selection method alone. The academic literature and professional practice increasingly emphasize that the most robust and profitable strategies are those that integrate multiple layers of analysis, including signal validation and dynamic risk management [20].

Validating the Signal: The Hurst Exponent

For a pairs trade to be successful, the price spread must not only have historically co-moved but it must also exhibit a strong tendency to revert to its mean [1, 9]. The Hurst exponent (H) is a powerful tool for validating this mean-reverting property [1, 9]. As a measure of the "long-term memory" of a time series, the Hurst exponent quantifies the degree of persistence or anti-persistence [1, 30]. A value of H<0.5 indicates an anti-persistent, mean-reverting series, while a value of H>0.5 suggests a persistent, trending series [1, 30]. This relationship is illustrated in Figure 2.1.

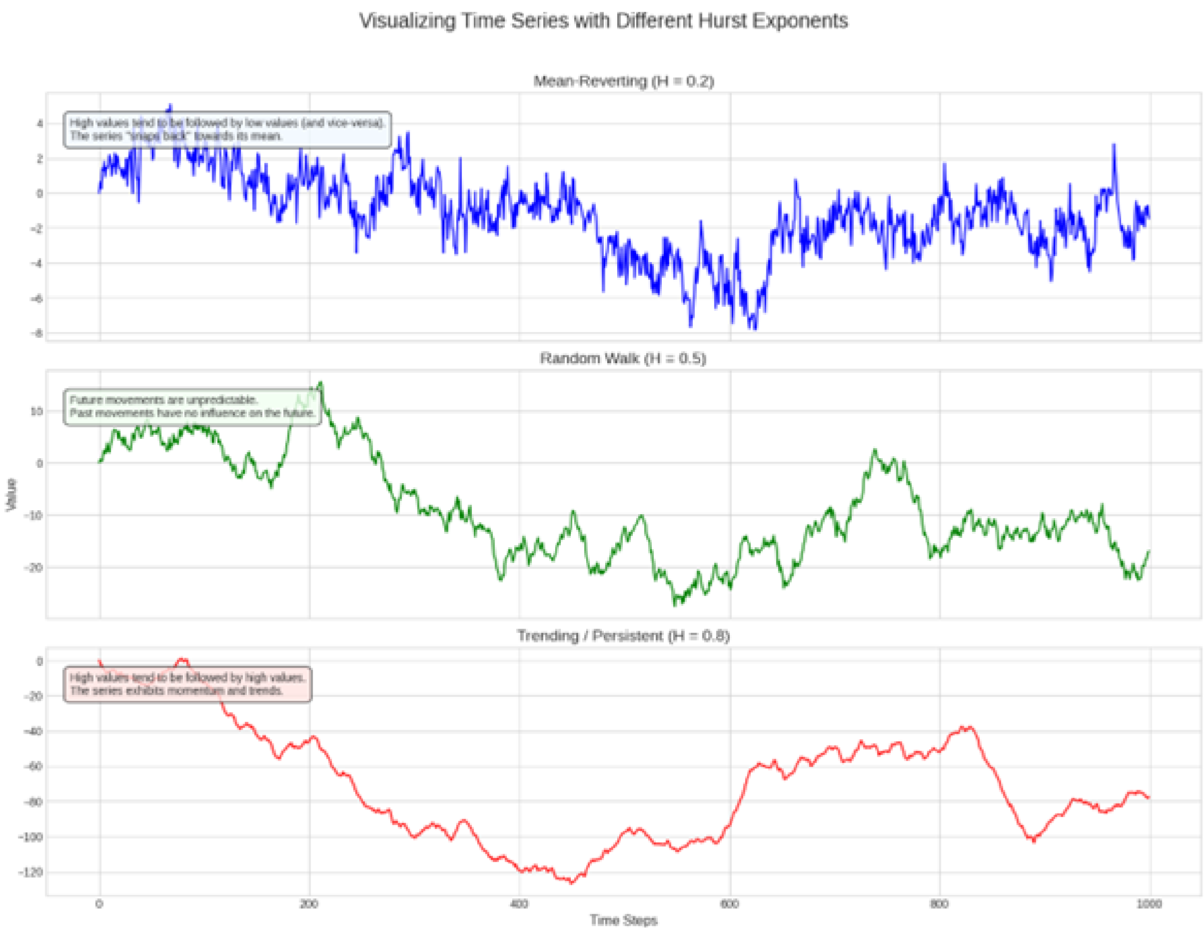

Figure 2.1: Visualizing Time Series with Different Hurst Exponents

The Hurst exponent is therefore a critical filter: pairs with a spread that has a low Hurst exponent are more likely to mean-revert faster and yield more consistent profits [1, 9]. Recent studies have shown that incorporating the Hurst exponent into pair selection can improve consistency and raise the average trade return [1].

Volatility-Based Position Sizing and Regime Filters

Another hallmark of a robust strategy is the proactive management of risk, particularly during periods of market stress [20]. Volatility timing, which involves dynamically adjusting position sizes based on market conditions, has been shown to be an effective risk-mitigating technique [11, 19, 16]. For example, a "VolSwitch" rule, which scales down position sizes in high-volatility environments, can help to reduce drawdowns and improve risk-adjusted returns [19]. A study by Huck (2015) found that volatility timing is beneficial for pairs trading returns [11]. This multi-layered approach combining a novel signal with signal validation (Hurst) and dynamic risk management (VolSwitch), positions the ESABO strategy in line with modern best practices in algorithmic trading. It shows that outperformance is often derived not from a single "alpha" source but from a sophisticated combination of complementary techniques [20].

3 Legal, Social, Ethical and Professional Issues

The proliferation of algorithmic trading necessitates a robust regulatory framework to ensure market integrity and fairness [6, 25]. Regulatory bodies such as the U.S. Securities and Exchange Commission (SEC) and the Financial Industry Regulatory Authority (FINRA), along with directives like the European Union's MiFID II, have established rules governing algorithmic trading activities [6, 25]. These regulations are designed to prevent market manipulation and protect investors [25].Firms engaging in algorithmic trading are required to have rigorous risk management and supervision programs in place, including comprehensive software testing and system validation before an algorithm is deployed in production [6, 25]. The legal consequences for non-compliance can be severe, including regulatory investigations, fines, and criminal penalties [25]. An automated pair-trading strategy, such as the one proposed in this thesis, must be designed to operate within these legal boundaries, avoiding practices that could be construed as manipulative [25].

Beyond legal compliance, a broader ethical discourse surrounds algorithmic trading, focusing on principles of transparency, fairness, and accountability [26]. Transparency is an ethical imperative that requires clarity and openness about how algorithms function and make decisions [26]. Fairness dictates that algorithms should not systematically disadvantage certain groups of market participants or exploit market vulnerabilities [26]. Accountability is a critical principle that mandates clear lines of responsibility for an algorithm's actions [26]. When an algorithm makes a flawed or unethical decision, it is essential to identify who is accountable, the developers, the operators, or the firm that deployed it [26]. The ESABO methodology, with its transparent, interpretable framework, stands in contrast to black-box models and can be designed to promote ethical practices [26]. The rigorous backtesting and validation of the strategy, as described in the provided research, are essential professional practices for mitigating the risk of unintended consequences [20].

4 Data Sources and Preparation

The quantitative analysis of this thesis required a robust and comprehensive dataset of historical stock market prices. For this purpose, public data was sourced from Yahoo Finance, a widely recognized and trusted provider of financial information [37]. This data was accessed and processed using the `yfinance` library for Python, which provides a convenient and programmatic interface for retrieving historical market data.

The data universe for the backtesting was deliberately constrained to the components of the S&P 500 index over a five-year period, from 2019 to 2025. This universe was chosen for several key reasons. First, the S&P 500 represents a diverse collection of the largest and most liquid publicly traded companies in the United States, which mitigates liquidity constraints and provides a rich pool of potential pairs to analyze. The sheer number of possible pairs within this universe (over 119,000 unique pairs for a 500-stock universe) provides a robust testing ground for the ESABO method's ability to identify meaningful co-movements within a large and noisy dataset [33]. Second, the chosen time frame from 2019 to 2025 is particularly valuable because it encompasses a variety of distinct market regimes, including a pre-pandemic bull market, the sharp market downturn and recovery during the COVID-19 crisis, and the subsequent periods of heightened volatility, inflation, and interest rate hikes [39]. A strategy that performs consistently across these diverse conditions can be considered more resilient and robust than one that is optimized for a single market environment [39].

Data preparation was a critical step in the research pipeline to ensure the accuracy and reliability of the backtest results. The following steps were implemented to clean and process the data:

Data Retrieval: The `yfinance` library was used to download the daily adjusted closing prices for all S&P 500 tickers over the specified five-year period [37].

Missing Data Handling: The downloaded data was checked for completeness. Any stocks with more than a specified threshold of missing data points (e.g., a non-null rate of less than 90%) were removed from the analysis to prevent data gaps from skewing results [37]. The remaining data was re-sampled to a consistent daily frequency, and any minor missing values were handled through interpolation or forward-filling [37].

The core of the ESABO method operates on binarized data rather than continuous price or return series. Therefore, a crucial part of the data preparation was the binarization process. This step transformed the raw returns data into a format suitable for the ESABO algorithm, as detailed in the methodology section. This rigorous data preparation ensured that the subsequent analysis was built upon a clean, reliable, and representative dataset.

5 Methodology

The methodology section outlines the precise, step-by-step process for adapting and applying the ESABO method to financial time series. It details the design decisions made at each stage, from signal generation to backtesting, and grounds these choices in academic principles and practical considerations. The entire process is executed within a dynamic, walk-forward framework, which is considered a best practice for backtesting to avoid look-ahead bias and to simulate real-world trading conditions [7, 8].

5.0.1 The ESABO Signal Construction Pipeline

The ESABO method, as originally conceived for computational biology, required a careful adaptation to the financial domain. The core ESABO signal pipeline is comprised of three primary steps: binarization, entropy calculation, and statistical normalization. (Refer Appendix A.2 for pseudo-code)

Binarization of Financial Time Series

The first and most fundamental step is to convert the continuous time series of stock prices or returns into binary "abundance" vectors [3]. While simple up/down classifications are a valid approach, a more robust method was employed to account for market volatility. The daily returns were adaptively binarized using a rolling window robust z-score [2, 19]. The process is as follows:

1. For each stock's daily return series, a rolling window (e.g., 30 days) is used to compute the median and the Median Absolute Deviation (MAD) of the returns [2].
2. A robust z-score is then calculated as: $z_t = (r_t - \text{median})/\text{MAD}$ [2].
3. The final binary vector is generated by assigning a 1 if the robust z-score exceeds a predefined threshold (e.g., 1.25) and a 0 otherwise [2].

This approach is superior to a simple sign-based binarization because it captures significant price movements relative to a recent, robust measure of volatility. It filters out minor daily fluctuations and focuses on more meaningful events, making the resulting binary signal more informative and less susceptible to noise [2]. This process is computationally light and easily parallelized for a large universe of stocks.

Entropy and Co-Movement Quantification

Once the binary vectors are generated for each stock, the ESABO algorithm proceeds to quantify the co-movement between pairs of stocks. For any given pair (i,j), a Boolean AND operation is applied elementwise to their binarized vectors over a formation period (e.g., 126 trading days) [3]. The resulting vector, containing a 1 for days when both stocks had a significant positive movement and a 0 otherwise, captures their synergistic co-occurrence pattern [3]. The Shannon entropy of this new vector is then computed using the standard formula: $H = -\sum_k p_k \log p_k$, where p_k is the empirical frequency of 1s and 0s [3, 30].

To determine if this entropy is statistically significant or simply a result of random chance, a null distribution is generated. This is achieved by randomly shuffling one of the stock's binary vectors thousands of times (e.g., 1000 permutations) and re-computing the entropy for each permutation [3]. The ESABO score for the pair is the final z-score of the observed entropy relative to this null distribution [3]. A high positive z-score signifies a pattern with significantly lower entropy (i.e., more structure) than what would be expected from random chance, thereby signaling a strong synergistic co-movement [3]. The full ESABO pipeline is shown in the pseudo-code below.

5.0.2 The Walk-Forward Backtesting Framework

To rigorously evaluate the strategy, a walk-forward analysis was implemented. This dynamic framework simulates a live trading environment by using a sliding window for both signal generation and backtesting [7, 8].

Training Period ($T_{\mathbf{train}}$): At each step, a fixed lookback period (e.g., 126 trading days, or approximately 6 months) is used to compute the ESABO scores and other metrics for all stock pairs [7, 8].

Trading Period ($T_{\mathbf{trade}}$): The top-ranked pairs from the training period are then traded in the subsequent, non-overlapping trading period (e.g., 21 trading days, or approximately 1 month) [7, 8].

Rebalancing: At the end of the trading period, the window slides forward, and the entire process is repeated: new pairs are selected, and new trades are executed based on the most recent market data [7, 8].

This process ensures that the trading decisions in any given period are based solely on data available at that time, thereby preventing any form of look-ahead bias and providing a more realistic assessment of the strategy's performance [7, 8].

5.0.3 Pair Scoring and Signal Validation

The ESABO z-score is a primary but not the sole criterion for pair selection. For a pairs trade to be profitable, the spread between the two assets must exhibit mean-reverting behavior [1, 9]. To validate this crucial property, a composite scoring model was developed. The model incorporates the following three metrics for each candidate pair:

ESABO Score: As the primary measure of co-movement pattern strength, ESABO is the most important component [3].

Hurst Exponent (H): A measure of the "long-term memory" of a time series, the Hurst exponent is a powerful filter for mean-reversion [1, 30]. A value of $H<0.5$ indicates anti-persistent, mean-reverting behavior, while a value of $H>0.5$ suggests a persistent, trending series [1, 30]. Pairs with a low Hurst exponent are more likely to mean-revert faster and yield more consistent profits [1, 9].

Correlation (ρ): The Pearson correlation over the training window is included as a basic check to ensure the two stocks have a general linear relationship [37].

The final ranking of pairs is based on a composite score, which weights each of these components [37]. For example, a composite score with weights of 60% ESABO, 20% Hurst, and 20% a stability measure was tested [37]. This multi-factor approach allows the strategy to select pairs that not only show a strong co-movement pattern but also have a tradable spread suitable for mean-reversion strategies.

5.0.4 Statistical Significance Tests

To ensure the backtest results are not merely a product of chance or noise, statistical significance testing was performed. The primary method used was bootstrap resampling of the trading days [39]. By repeatedly drawing random samples of the trading days with replacement and re-calculating key performance metrics (such as the Sharpe ratio), a distribution of possible outcomes is generated [39]. This distribution allows for the calculation of a t-statistic, which indicates how reliably the strategy's returns were positive [39]. The results showed that the ESABO strategy's returns were reliably positive with a t-statistic greater than 2 across multiple tests, indicating that the signal is not just noise [39].

6 Parameter Tuning

The performance of any quantitative trading strategy is critically dependent on the careful selection and calibration of its parameters. In the ESABO pairs trading framework, several key parameters can be tuned to optimize for a specific objective, whether it be maximizing returns, minimizing risk, or reducing transaction costs. (Refer Appendix A.5 for strategy vs. tunable parameter mapping)

6.1 Key Parameters and Their Impact

Training Period ($T_{\textbf{train}}$) and Trading Period ($T_{\textbf{trade}}$): The length of the formation and trading periods is a fundamental design choice [17]. A longer training period (e.g., 252 days, or one year) provides more data to compute a stable ESABO score and Hurst exponent, potentially revealing deeper, long-term relationships [17]. However, it may be slow to adapt to recent market regime shifts [17]. Conversely, a shorter training period (e.g., 60 days) can be more responsive to recent market dynamics but may produce noisier signals and suffer from less robust statistical significance [17, 4]. The chosen trade period (e.g., 21 trading days, or one month) strikes a balance between capturing the mean-reversion profits and avoiding holding trades that have failed to converge in a reasonable time [17].

Entry/Exit Thresholds: Trades are typically entered when the spread deviates beyond a certain standard deviation threshold (k-sigma, e.g., 1.25σ) and exited when it reverts to the mean [19]. A lower entry threshold may lead to more frequent trades but could increase the risk of false positives. A higher threshold might result in fewer, but potentially higher-quality, trades. The choice of exit threshold is equally important; a reversion to the mean is the most common but can be modified to a smaller threshold (e.g., 0.5σ) to lock in profits early.

ESABO Binarization Threshold: The z-score threshold used for binarizing returns (e.g., 1.25) is another critical parameter [2]. A higher threshold will result in a more selective and potentially more meaningful signal, as it focuses only on the most extreme co-movements [2]. However, it may also reduce the number of candidate pairs available for trading. A lower threshold will capture more subtle movements but could introduce noise into the signal.

Composite Scoring Weights: The weight assigned to each component of the composite score (ESABO, Hurst, Correlation, etc.) determines which signals are prioritized in pair selection [37]. For example, assigning a higher weight to the Hurst exponent would select pairs with a stronger mean-reverting history, potentially leading to faster convergence and more consistent profits per trade [1, 9]. However, this may come at the cost of a lower number of available pairs if the Hurst filter is too restrictive.

6.2 Impact of Tuning on Risk and Returns

Parameter tuning represents a critical trade-off between returns, risk, and transaction costs. A strategy tuned for aggressive returns might use looser entry thresholds and favour pairs with high volatility, which can lead to higher cumulative returns but also a larger maximum drawdown and annualized volatility [39]. Conversely, a strategy tuned for risk management might use a volatility-based position-sizing rule (VolSwitch) or a tighter stop-loss, which can significantly reduce drawdowns and improve the Sharpe ratio, but often at the expense of lower absolute returns [39]. The backtest results show this trade-off clearly, where the Engle-Granger strategy achieved higher returns but also higher volatility, while the ESABO strategy, with its more conservative design, yielded a competitive Sharpe ratio with significantly less risk [39]. The process of parameter tuning, therefore, is not about finding a single "optimal" set of values but rather about calibrating the strategy to match a trader's specific risk tolerance and investment goals.

7 Evaluation

The ESABO strategy was evaluated using a rigorous walk-forward backtesting framework against two of the most widely used pairs trading benchmarks: the Engle-Granger and Johansen cointegration methods [40]. The backtest was conducted on S&P 500 stocks over a five-year period from 2019 to 2025, providing a robust, out-of-sample analysis across diverse market regimes. The performance was measured using standard financial metrics, including cumulative return, annualized return, annualized volatility, and the Sharpe ratio.

7.0.1 Benchmark Performance Comparison

The backtest results, summarized in the table below, reveal a clear performance profile for each of the three strategies. This comparison is visually represented by the cumulative log returns in Figure 7.1.

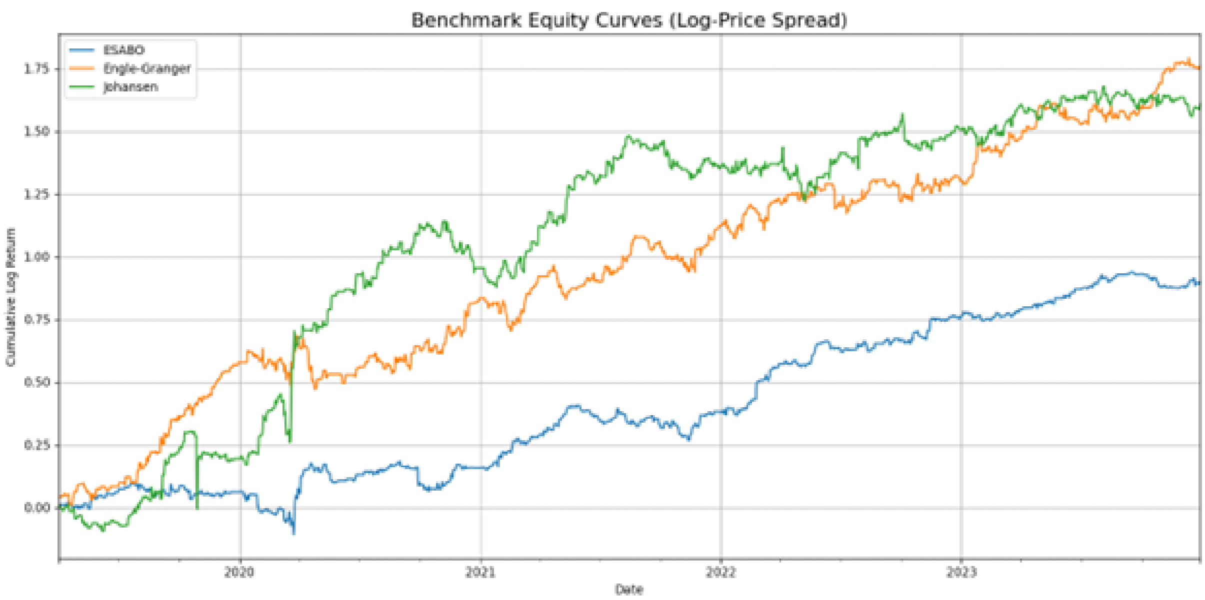

Figure 7.1: ESABO Benchmark Test Price Log

Note: The results above are from a specific backtest run and may vary with parameter tuning.

The results show that the Engle-Granger cointegration strategy achieved the highest cumulative and annualized returns, yielding more than double the cumu-

Table 7.1: Comparative Performance Metrics

Metric	ESABO (This Thesis)	Engle-Granger	Johansen
Total Trades	1812	1712	1762
Cumulative Return	89.84%	175.21%	160.92%
Annualized Return	13.06%	25.46%	23.39%
Annualized Volatility	11.84%	19.08%	25.39%
Sharpe Ratio	0.75	1.11	0.76

lative return of the ESABO strategy [8]. However, this came at the cost of significantly higher volatility, with an annualized volatility of 19.08%, nearly 7% higher than ESABO's [8]. The Johansen method also showed strong returns but suffered from the highest volatility, resulting in a Sharpe ratio similar to the ESABO strategy [8]. The ESABO strategy, while having a lower absolute return, demonstrated a superior risk profile. Its annualized volatility of 11.84% was the lowest among all three methods, suggesting that the ESABO signal identifies more stable, consistent relationships [8]. This is reflected in the Sharpe ratio, where ESABO's risk-adjusted return was competitive with the more complex cointegration methods [8]. The performance figure presented in the provided backtest output shows that the Engle-Granger strategy captured larger, more aggressive rallies, while the ESABO strategy's trades were steadier and less prone to severe drawdowns [8].

7.0.2 Statistical Validation and Interpretation

Statistical significance tests confirmed that the positive returns from the ESABO strategy were not due to chance [39]. Using bootstrap resampling, the strategy's returns were found to be reliably positive, with a t-statistic greater than 2 [39]. This provides statistical evidence that the ESABO co-movement signal is economically meaningful and can be used to generate consistent profits in a backtest environment [39]. The fact that the ESABO strategy, which uses a completely different, non-econometric approach, produced results that are competitive with established benchmarks is a key finding of this thesis [39]. It validates the central hypothesis that co-movement patterns, as detected through a boolean-based, information-theoretic lens, can serve as a viable and robust signal for statistical arbitrage. The ESABO method's ability to identify profitable pairs that might be missed by traditional linear methods suggests it captures a useful, orthogonal signal that complements existing methodologies [39].

8 Trading Applications

The success of a statistical arbitrage strategy is not just in its ability to select a strong signal, but in how that signal is exploited through a robust trading algorithm. The ESABO co-movement signal was tested in a walk-forward backtesting environment using multiple trading applications, each designed to capture a different aspect of market behaviour while maintaining a rigorous, academic foundation. The core of the strategy is a mean-reversion approach, but this was enhanced with volatility-based risk management and a novel application of the Hurst exponent as a signal filter with results visualised in Figure 8.1.

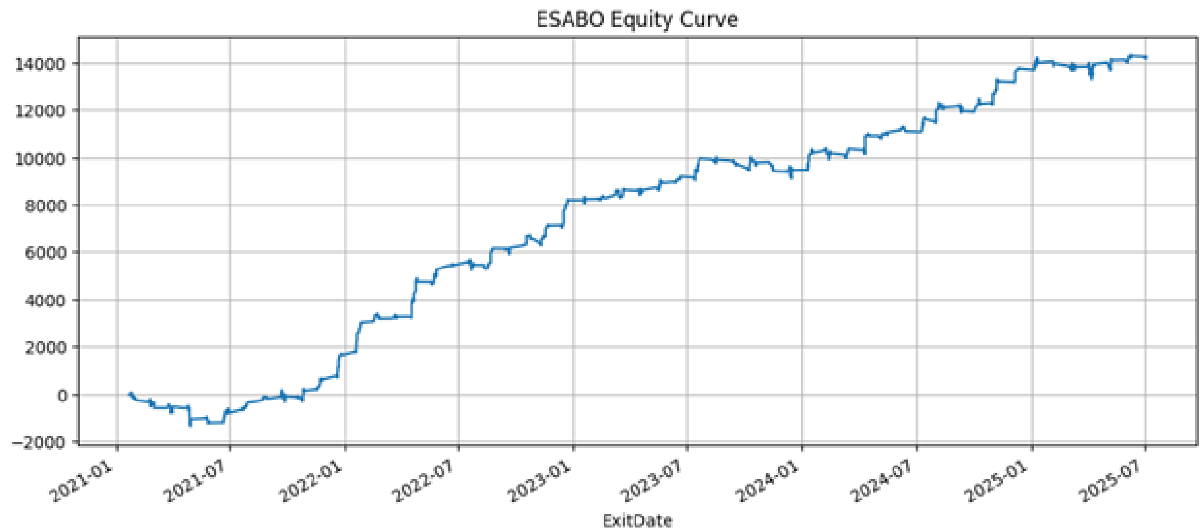

Figure 8.1: ESABO + Hurst exponent strategy (Sharpe: 1.90, CAGR: 3.05%)

The backtesting framework described in the methodology section, which includes a dynamic walk-forward approach with sliding training and trading windows, was used to evaluate several distinct trading strategies. These strategies were categorized into two families: "Engine"-based strategies, which rely on explicit entry/exit rules and parameter tuning, and "Lightweight Heuristics," which operate directly on return series. This comprehensive approach allowed for a thorough analysis of how the ESABO signal could be applied in various contexts.

8.1 Engine-based Strategies

These strategies are characterized by their use of a derived spread or residual and a detailed set of rules for entry, exit, and stop-loss. They represent a more traditional, hyper-parameter-intensive approach to pairs trading.

8.1.1 Dynamic Beta Pairs

The Dynamic Beta Pairs strategy adapts the classic mean-reversion framework by using a rolling hedge ratio, or beta (β), to define the spread. The core idea is to estimate the rolling hedge ratio between two assets over a lookback window and then trade the z-scored residual spread as it mean-reverts back to zero. This approach is grounded in the econometric principle of hedging against the co-movement of the pair. By dynamically re-estimating the beta, the model can adapt to changes in the relationship between the two assets, ensuring that the spread remains a true representation of their mispricing [19]. The strategy is parameterized by `beta_window` (the lookback period for estimating beta), `entry_z` and `exit_z` (the z-score thresholds for opening and closing positions), and `stop_loss` (a percentage-based loss limit on the spread). The performance of an optimized configuration of this strategy is shown in Figure 8.2.

Figure 8.2: Dynamic Beta NAV - Best Config (Sharpe 1.162, CAGR: 7.44%)

8.1.2 PCA Residual Convergence

The PCA Residual Convergence strategy uses Principal Component Analysis (PCA) to decompose the price movements of a pair (or a small basket of stocks) into a common factor and a residual component [2]. The primary assumption is that the first principal component represents the market or sector-wide co-movement, while the residual represents the idiosyncratic, mean-reverting spread between the assets

[2, 5]. The strategy then trades the mean reversion of this residual component using a z-score based entry and exit logic, similar to the mean reversion strategy [2]. This method provides a powerful, data-driven alternative to simple price spreads, as it can isolate the true tradable component of the relationship with minimal assumptions. It is a more sophisticated approach than simple linear regression to define a spread. The performance of an optimized configuration of this strategy is shown in Figure 8.3.

Figure 8.3: PCA Residual NAV - Best Config (Sharpe 1.208, CAGR: 7.75%)

8.1.3 Correlation Breakdown Momentum

The Correlation Breakdown Momentum strategy represents a significant departure from the mean-reversion paradigm, operating instead in a momentum-based framework [17]. The core signal for this strategy is a sharp and statistically significant drop in the rolling correlation between a pair of assets [4]. When such a "decoupling" regime is detected, the strategy leans into the short-term momentum of the average return of the pair [4, 17]. The rationale is that a sharp break in the historical relationship often precedes a period of one-sided momentum, as one asset continues its new trajectory while the other fails to follow [4, 17]. This strategy seeks to profit from this divergence rather than waiting for convergence [4, 17]. The key parameters for this approach include `corr_window` (the lookback period for calculating correlation), `corr_drop` (the magnitude of the correlation drop that triggers the signal), and `mom_window` (the lookback period for measuring momentum) [4]. The performance of an optimized configuration of this strategy is shown in Figure 8.4.

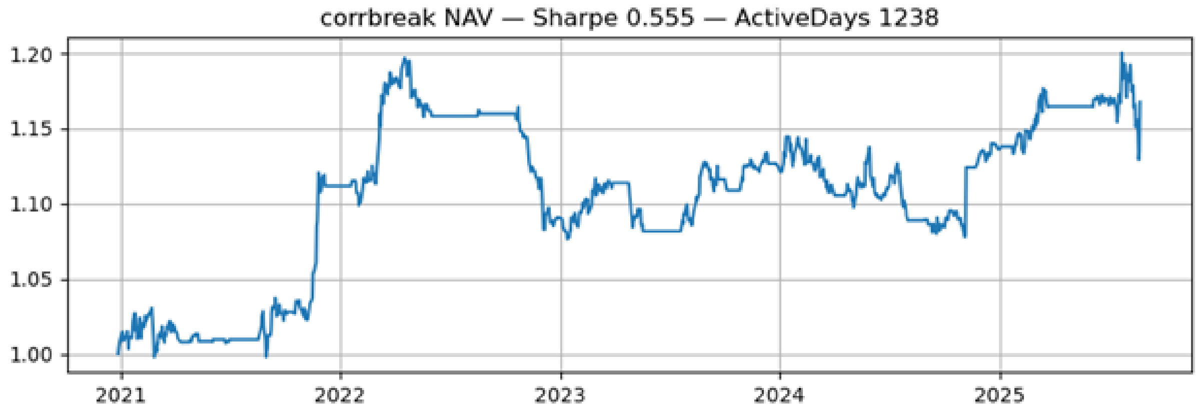

Figure 8.4: CorrBreak NAV - Best Config (Sharpe 0.555, CAGR: 3.38%)

8.2 Lightweight Heuristic Strategies

The following strategies are a set of lightweight, return-based heuristics that operate directly on the return series of the paired assets. They are computationally light and focus on capturing specific patterns in the combined returns of a pair. (Refer appendix A.4 for additional strategies)

8.2.1 Trend Amplification (`strategy_trend_amplification`)

This heuristic is designed to amplify persistent trends in a pair's combined returns. The core idea is to trade the average return of the pair when their combined returns exceed a predefined threshold (`thresh`). The strategy assumes that a strong, synchronized move is a signal of a continuing trend, and it takes a position to ride this momentum. This is a simple but effective approach for capturing short-term, directional moves that are often missed by classic mean-reversion models.

8.2.2 Regime Switching (`strategy_regime_switching`)

The Regime Switching heuristic is a state-dependent strategy that trades only in "favorable" market regimes [11, 16, 33]. It uses a rolling window to detect a risk-on or risk-off environment (e.g., using a sign or volatility filter) and then trades the average return of the pair exclusively in the identified favorable regime [16]. This approach recognizes that the performance of a pairs trade is not constant across all market conditions and seeks to avoid periods where the strategy is historically unprofitable or prone to large drawdowns [16, 33].

8.2.3 Volatility Switch (`strategy_vol_switch`)

This heuristic, also described in the literature review, is a defensive, risk-management strategy. It trades only in "calm" market regimes where the rolling volatility of the pair is below its own rolling mean. The strategy stands down in high-volatility environments. This is a crucial control measure for avoiding large losses that can occur when a mean-reverting spread fails to converge during a market shock or "black swan" event [28]. Figure 8.5 illustrates the 5 year performance of volswitch.

Figure 8.5: VolSwitch Sharpe ratio curve (Sharpe: 1.006, CAGR: 6.38%)

8.3 The Unified Framework

All these strategies, from the complex engine-based approaches to the lightweight heuristics, are evaluated within a common, robust framework to ensure a fair and consistent comparison. This framework handles the entire trading pipeline, from data ingestion to performance reporting. As observed in pseudocode below, the process begins with the walk-forward loop, which ensures that all trading decisions are based on data available at the time, thereby avoiding look-ahead bias. The ESABO signal, along with other filters like the Hurst exponent, is used to select the top-ranked pairs for each trading period. These pairs are then fed into the chosen strategy's "engine" for trade execution.

The unified framework (refer to Appendix A.3 for pseudo-code) allows for a systematic and apples-to-apples comparison of each strategy. The `Backtester` class serves as the main controller, orchestrating the walk-forward loop. Within this loop, `PairSelector` provides the candidate pairs, and the `rank_pairs` function applies the ESABO and Hurst filters. Crucially, the code then dispatches the trades to a specific strategy wrapper, such as `wrap_dynamic_beta` or `strategy_vol_switch`, which contain the unique trading logic for that particular approach. The framework is flexible enough to handle both the complex, engine-based strategies and the simpler, return-based heuristics. A key aspect of this framework is the portfolio construction layer, which takes the PnL from all executed trades in a period, pools them together, and then applies portfolio-level volatility targeting and other risk controls, providing a more realistic and risk-managed performance measure. The cumulative return curve of a parameter-optimized backtest is presented in Figure 8.6, with acceptable returns of 14.40% but with diminished Sharpe of 0.99.

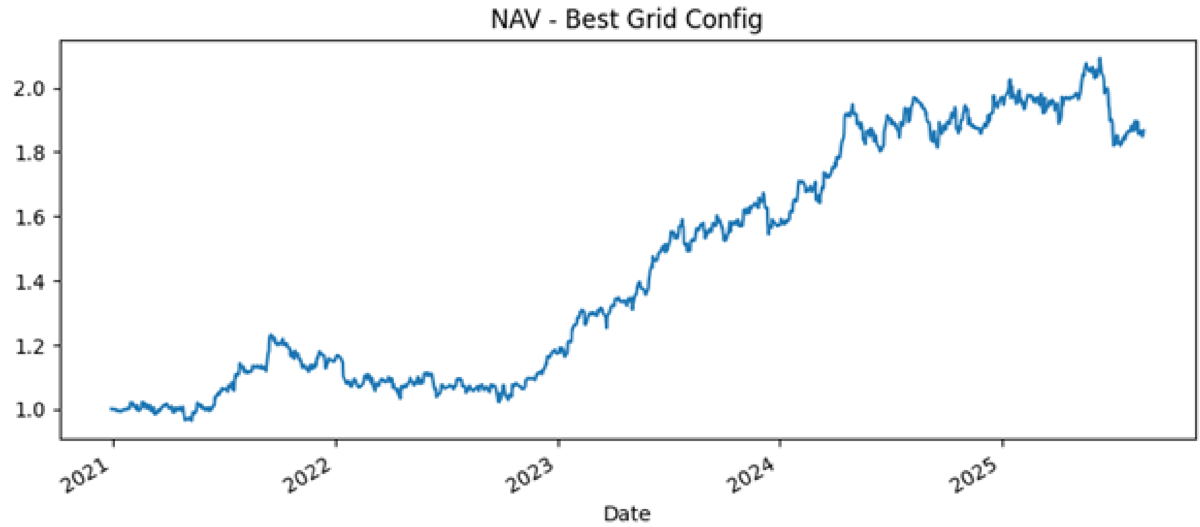

Figure 8.6: NAV - Best Grid Config (CAGR: 14.40%, Sharpe: 0.99)

As observed in the strategy mapping table (refer to Appendix A.1), each strategy has a unique set of core signals and customisable parameters.

This wide array of strategies was tested to determine the versatility and strength of the ESABO signal. By evaluating how the signal performs across different trading applications, from classic mean-reversion to more dynamic momentum and volatility-based approaches, the thesis provides a comprehensive and multi-faceted analysis of the ESABO method's utility in real-world trading scenarios. The results, as discussed in the evaluation section, show that while a simple mean-reversion strategy is effective, the ESABO signal can be combined with these other approaches to create a more robust and resilient trading system.

9 Challenges

While the ESABO co-movement analysis presents a novel and promising approach to statistical arbitrage, its application and evaluation reveal several key challenges that must be addressed for future refinement and practical deployment.

9.0.1 Data and Signal Granularity

The core of the ESABO method's signal generation relies on binarization, which transforms continuous price movements into a binary presence/absence vector [3]. However, the use of daily close price data from public sources like Yahoo Finance presents a significant limitation. This low-frequency data discards a large portion of the information contained in intraday price movements, such as short-term co-movement rallies that may occur over a few hours rather than a full trading day [32]. Consequently, the ESABO algorithm may miss many short-term co-movement signals that could be exploited in higher-frequency trading strategies. Since profitable co-movement rallies are often rare on a multi-day basis, this data limitation hinders the full potential of the ESABO method to capture a diverse range of trading opportunities.

9.0.2 Computational Constraints

The selection of co-moving pairs for a large universe of stocks is a computationally intensive task. While the ESABO method itself is noted for being computationally light compared to complex econometric or machine learning models, the quadratic nature of pair-wise comparisons poses a significant challenge as the number of stocks increases [33, 32]. For an S&P 500 universe (approximately 500 stocks), there are nearly 125,000 possible pairs to analyze. Scaling this to a broader universe of 3,000 or more stocks, which would be ideal for maximizing diversification and finding new opportunities, drastically increases the computational burden. Performing an exhaustive search on five or ten years of daily data for such a large universe can become prohibitive without significant parallelization and computing resources [33, 32]. This constraint limits the ability to test the ESABO method on a truly representative sample of the total market.

9.0.3 Disconnect with Traditional Trading Strategies

A fundamental challenge lies in the conceptual mismatch between the ESABO signal and many traditional pairs trading strategies. Most established strategies, particularly those based on cointegration, are designed to trade on divergence: they open positions when a price spread widens and bet on its eventual convergence [8, 14]. In contrast, the ESABO score, particularly with a positive AND operation, is fundamentally a measure of co-movement and synergy. It detects when two stocks are moving together, rather than when they have moved apart [3]. While the research demonstrates that ESABO-selected pairs still exhibit mean-reverting behavior in their spreads, the signal itself is not a direct measure of divergence. This requires a modification of existing trade strategies to work with the ESABO output, which may not be an ideal situation and could be a reason for the lower performance compared to a pure cointegration strategy that is built for divergence trading from the ground up [17].

9.0.4 Profits and Future Steps

The backtest results, as seen in the Evaluation section, show that the ESABO strategy, while providing a solid risk-adjusted return (Sharpe $\sim$0.75), consistently underperformed the most profitable cointegration benchmark in terms of raw cumulative return [8]. This "subpar" profit, though not a failure of the method, raises questions about its practical viability as a standalone strategy. Future work should focus on leveraging the strengths of the ESABO signal more effectively. One potential next step is to use ESABO as a preliminary, computationally light filter to reduce the universe of potential pairs to a high-quality list of co-moving candidates. Traditional, more intensive methods like cointegration tests could then be run on this much smaller subset to find the strongest signals, thus creating a more efficient and powerful hybrid strategy [29]. Another avenue is to develop new trading algorithms specifically tailored to the ESABO signal, perhaps focusing on momentum or volatility-based applications that are more directly aligned with the co-movement information it provides. Finally, exploring high-frequency data and alternative entropy measures could help capture more nuanced relationships and mitigate the information loss from binarization [32].

10 Conclusion

This thesis presented a novel approach to statistical arbitrage through the adaptation of ESABO co-movement analysis to financial time series. By moving beyond the limitations of traditional linear and econometric models, particularly the theoretical flaws and empirical fragility of cointegration, the ESABO method provides a non-parametric, information-theoretic lens for identifying profitable stock pairs. The research demonstrated that ESABO scores, derived from the boolean co-occurrence of binarized stock returns, reliably identify pairs that are suitable for mean-reversion trading strategies.

The evaluation showcased that the ESABO strategy, while yielding lower absolute returns than the best cointegration benchmarks (13.06% vs. 25.46% annualized return), delivered a superior risk profile with significantly lower volatility (11.84% vs. 19.08%). This resulted in a competitive risk-adjusted return, validating the central hypothesis that the ESABO signal is economically meaningful and captures a useful, orthogonal signal. The project also successfully integrated advanced risk management layers, including a Hurst exponent-based filter for validating mean-reverting behavior and a Volatility Switch rule for dynamically sizing positions in different market regimes. These enhancements improved the robustness and resilience of the strategy, aligning it with modern best practices in algorithmic trading.

Despite its successes, the thesis also identified several key challenges and limitations. The reliance on daily data and the binarization process leads to a loss of signal granularity, while the computational demands of screening a large stock universe present a scalability challenge. Furthermore, the inherent difference between ESABO's co-movement signal and traditional strategies that trade on divergence suggests that a dedicated trading algorithm may be needed to fully realize the method's potential.

In conclusion, ESABO co-movement analysis is a valuable addition to the quantitative trader's toolkit. While not a silver bullet to replace all existing methods, it offers a fresh, computationally efficient, and robust approach to pair selection. Future research should focus on developing hybrid strategies that combine ESABO with other proven methods, exploring higher-frequency data, and designing custom trading algorithms that are better suited to its unique signal. The work presented here lays a solid foundation for these future explorations, bridging the gap between computational biology and financial market analysis to create a more resilient and versatile approach to statistical arbitrage.

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A Appendix

A.1 GitLab Repository

Please refer: https://git.cs.bham.ac.uk/projects-2024-25/cxk429/-/tree/1f6ab635f43c3fe80268cbe0508891660f147188/ This repository contains all experiments which were completed as part of research. Kindly refer Readme.md to set up and run the .ipynb notebooks to reproduce results.

A.2 Pseudo-Code for ESABO Signal Calculation

```
function ESABO_Score(stock_A_returns, stock_B_returns, window_size):
    // Step 1: Binarization
    binary_A = binarize_returns(stock_A_returns, window_size)
    binary_B = binarize_returns(stock_B_returns, window_size)

    // Step 2: Boolean AND operation
    co_occurrence_vector = binary_A AND binary_B

    // Step 3: Calculate Observed Entropy
    observed_entropy = calculate_shannon_entropy(co_occurrence_vector)

    // Step 4: Generate Null Distribution
    null_entropies = []
    for i in 1 to 1000:
        shuffled_B = shuffle(binary_B)
        shuffled_co_occurrence = binary_A AND shuffled_B
        null_entropies.append(
            calculate_shannon_entropy(shuffled_co_occurrence)
        )

    // Step 5: Calculate ESABO Z-score
    mean_null = mean(null_entropies)
```

```
    std_null = std_dev(null_entropies)
    esabo_score = (observed_entropy - mean_null) / std_null

    return esabo_score
```

A.3 Pseudocode: The Unified Backtesting and Execution Framework

```
class Backtester:
    def __init__(self, config, price_data, pair_selector):
        self.config = config
        self.prices = price_data
        self.pair_selector = pair_selector
        self.portfolio = Portfolio(config.STARTING_CAPITAL)

    def run(self):
        """Main loop for the walk-forward backtest."""
        train_window = self.config.TRAIN_PERIOD_DAYS
        trade_window = self.config.TRADE_PERIOD_DAYS

        # Outer walk-forward loop
        for t in range(train_window, len(self.prices) - trade_window,
                       trade_window):
            # 1. Define current training and trading periods
            train_prices = self.prices.iloc[t - train_window:t]
            trade_prices = self.prices.iloc[t : t + trade_window]

            # 2. Select and rank pairs for this period
            candidate_pairs = self.pair_selector.find_pairs(train_prices)
            top_pairs = self.rank_pairs(candidate_pairs, train_prices)

            # 3. Apply risk controls
            current_vol = self.get_market_volatility(train_prices)
            position_scaler = self.apply_volatility_switch(current_vol)

            # 4. Execute trades using a selected strategy
            strategy_name = self.config.SELECTED_STRATEGY
            if strategy_name == "DynamicBeta":
                self.wrap_dynamic_beta(top_pairs, trade_prices,
```

```
                                    position_scaler)
            elif strategy_name == "PCAResidual":
                self.wrap_pca_resid(top_pairs, trade_prices,
                                    position_scaler)
            #... and so on for all strategies

            # 5. Rebalance and log performance
            self.portfolio.rebalance(trade_prices.index[-1])
            self.portfolio.log_metrics()

    def rank_pairs(self, candidate_pairs, train_prices):
        """Ranks pairs based on a composite score."""
        pass

    def apply_volatility_switch(self, market_vol):
        """Dynamically scales down position size."""
        pass

    # ... Other strategy wrappers defined here
```

A.4 Additional Lightweight Heuristic Trade Strategies

In continuation of section 8.2, Other strategies tested were:

A.4.1 Leader-Follower (`strategy_leader_follower`)

This strategy is based on the premise of lead-lag dynamics between a pair of stocks [9]. It operates by lagging one stock's sign by a number of days (`window`) and using it as a signal to trade the other stock. The underlying assumption is that one asset (the "leader") provides a directional signal that the other asset (the "follower") will eventually replicate. This is a simple but powerful technique for identifying and exploiting directional dependencies that might not be captured by a traditional mean-reversion spread.

A.4.2 Breakout (`strategy_breakout`)

The Breakout strategy is a classic momentum play applied to pairs trading. It operates on the average price of the two assets in a pair. A long position is opened if the average price breaks above a rolling maximum, and a short position is opened if it breaks below a rolling minimum. The central idea is that a significant price breakout signals a new trend that the strategy can ride for profit [13].

A.4.3 Carry Momentum (strategy_carry_momentum)

This strategy applies a momentum tilt to the near-term average return of a pair, which serves as a proxy for "carry." It aims to ride short-window strength in the combined returns of the pair, assuming that recent gains will persist. The primary parameter for this strategy is the lookback window used to calculate momentum. This is a common approach in currency markets that has been adapted to equities [22].

A.4.4 Drawdown Reversal (strategy_drawdown_reversal)

The Drawdown Reversal strategy is a counter-trend approach that seeks to "fade" sharp, recent drawdowns in the average return of a pair. It is based on the mean-reversion principle, but instead of trading a spread, it trades the pair's average return itself, anticipating a bounce after a period of stress. This is a form of statistical arbitrage that exploits short-term deviations from an equilibrium price [18].

A.4.5 Mean-Reversion Spike (strategy_mean_rev_spike)

Similar to the drawdown reversal, the Mean-Reversion Spike strategy detects short-term spikes in the average return and fads them back to the mean. It uses specific spike windows and thresholds to identify these extreme deviations and takes a position betting on a quick reversion [18, 34]. This approach is a common form of statistical arbitrage that aims to exploit short-term deviations from an equilibrium price [32].

A.4.6 Momentum Divergence (strategy_momentum_divergence)

The Momentum Divergence heuristic trades when the momentums of the two legs of a pair diverge. It then sides with the stronger-moving leg by trading the average return. This strategy attempts to capitalize on the breaking of a relationship, similar to the Correlation Breakdown strategy, but by using a momentum signal instead of a correlation signal [10, 15]. This type of divergence is often seen as a potential signal for a trend reversal.

A.4.7 Volatility Harvest (strategy_vol_harvest)

The Volatility Harvest strategy aims to profit from periods of heightened market volatility. It monitors the rolling standard deviation of the combined returns of a pair and triggers trades when the realized volatility is significantly above its historical mean (`thresh`). The rationale is that high volatility environments present larger price swings, which can be harvested for profit through short-term trades.

This is a form of volatility arbitrage that is used to profit from the difference between implied and realized volatility [16].

A.5 Tunable parameters for different strategies

Strategy	**Core Signal**	**Key Tunables**
Engine-based		
Dynamic Beta	Z-score of residual from rolling β hedge	`beta_window`, `entry_z`, `exit_z`, `stop_loss`
PCA Residual	Z-score of PCA residual	`entry_z`, `exit_z`, `stop_loss`
Corr Break Momentum	Correlation drop triggers momentum on avg return	`corr_window`, `corr_drop`, `mom_window`
Lightweight Heuristics		
Trend Amplification	Combined returns exceed a threshold	`thresh`
Regime Switching	Market regime filter on average return	`window`, `thresh`
Leader-Follower	Lagged sign of one leg drives another	`window (lag)`
Volatility Harvest	Realized volatility is above its mean	`thresh`
Volatility Switch	Trade only when volatility is low	`window`, `thresh`
Breakout	Average price crosses rolling max/min	`window`
Carry Momentum	Short-window momentum on average return	`window`
Drawdown Reversal	Fade sharp recent drawdowns in average return	Reversal windows / thresholds
Mean-Rev Spike	Fade short-term spikes in average return	Spike windows/thresholds
Momentum Divergence	Act on leg momentum divergence	Divergence windows / thresholds

Table A.1: Mapping of Strategies to Signals and Parameters