Dual Spread Confirmation Framework for Robust Pairs Trading

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***Abstract*—Pairs trading is a widely adopted statistical arbitrage strategy that relies on the mean-reverting behavior of correlated asset pairs. However, traditional approaches based on a single spread—either static or dynamic—often suffer from noise, unstable signals, and excessive trading frequency. This paper proposes a Dual Spread Confirmation Framework (DSCF) that integrates both long-term (static) and short-term (dynamic) spread representations to enhance signal reliability. The proposed framework generates trading signals only when both spreads simultaneously indicate significant deviation, thereby filtering out spurious market movements. Empirical analysis on equity pairs demonstrates that the DSCF approach delivers improved risk-adjusted performance compared to conventional methods. Additionally, the proposed model effectively reduces maximum drawdown and trading frequency, indicating enhanced stability and robustness. The results highlight that incorporating a dual confirmation mechanism can mitigate noise in dynamic models while preserving adaptability. This study establishes DSCF as a simple yet effective enhancement to traditional pairs trading strategies, with strong potential for practical financial applications.**

***Index Terms*—Pairs Trading, Statistical Arbitrage, Dual Spread, Signal Confirmation, Rolling Regression, Risk Management**

I. INTRODUCTION

Pairs trading is a well-established statistical arbitrage strategy that exploits temporary deviations between the prices of two historically correlated assets [1], [3]. The core assumption underlying this strategy is that the spread between such assets exhibits mean-reverting behavior, allowing traders to profit from divergence and subsequent convergence. Early empirical studies demonstrated the effectiveness of simple distance-based and cointegration-based approaches in generating consistent returns in equity markets [1]. Traditional pairs trading models primarily rely on a static hedge ratio, estimated using techniques such as Ordinary Least Squares (OLS), to define a long-term equilibrium relationship between asset prices. While these approaches are simple and computationally efficient, they assume stationarity in asset relationships, which often does not hold in real-world financial markets characterized by structural changes and regime shifts [4].

To address this limitation, dynamic approaches such as rolling regression and state-space models have been proposed to capture time-varying relationships between assets [6], [11]. Although these methods improve adaptability, they often introduce noise and instability in the estimated spread, leading to frequent trading signals and increased transaction costs. This trade-off between stability and adaptability remains a key challenge in pairs trading research. Recent advancements in statistical arbitrage emphasize the importance of signal filtering and robustness [8], [12]. However, most existing methods rely on a single spread representation, either static or dynamic, which limits their ability to distinguish between genuine trading opportunities and noise-induced fluctuations. Furthermore, several studies have explored extensions such as cointegration and econometric-based approaches to enhance robustness [4], [8].

To overcome these limitations, this paper proposes a DSCF that integrates both static and dynamic spread representations. The key innovation lies in executing trades only when both spreads simultaneously indicate significant deviation, thereby introducing a confirmation mechanism that enhances signal reliability. By combining the stability of static models with the adaptability of dynamic models, the proposed framework effectively reduces noise, minimizes overtrading, and improves risk-adjusted performance. The effectiveness of the proposed approach is validated through empirical analysis, demonstrating superior performance in terms of Sharpe ratio, drawdown, and trading efficiency compared to conventional methods.

The remainder of the paper is structured as follows: Section 2 provides a comprehensive review of the existing literature, highlighting key developments and research gaps. Section 3 details the proposed approach and its underlying methodology. Section 4 presents the experimental results along with a thorough discussion and analysis. Finally, Section 5 concludes the study and outlines potential directions for future research.

II. LITERATURE SURVEY

Pairs trading, also known as statistical arbitrage, is a widely studied trading strategy that exploits temporary deviations between the prices of two correlated assets. The strategy is based on the assumption that the price spread between such assets follows a mean-reverting process [1], [3]. Over the years, various approaches have been developed to improve the effectiveness and robustness of pairs trading. One of the earliest systematic approaches was proposed by Gatev et al., who introduced the distance-based method for selecting trading pairs based on minimum historical price distance [1]. Their study demonstrated that such strategies could generate consistent excess returns. However, the distance-based approach does not explicitly model the equilibrium relationship between assets, which may lead to unstable pair selection and inconsistent performance under changing market conditions [4].

To overcome these limitations, cointegration-based models were introduced, which establish a long-term equilibrium relationship between asset prices and ensure mean-reverting behavior of the spread. Vidyamurthy provided a comprehensive framework for cointegration-based pairs trading [3]. While these models offer a strong theoretical foundation, they assume a static relationship between assets, which may not hold in dynamic and evolving financial markets [7]. In order to capture time-varying relationships, dynamic approaches such as rolling regression and state-space models have been proposed. These methods allow the hedge ratio to vary over time, thereby improving adaptability to changing market conditions [11]. Techniques such as Kalman filtering are widely used for estimating dynamic hedge ratios. Although these approaches enhance flexibility, they often introduce noise and instability in the spread, leading to frequent and unreliable trading signals [6], [9].

Recent advancements in statistical arbitrage have focused on improving signal quality through advanced filtering and regime-based models. Approaches such as Hidden Markov Models (HMM), regime-switching models, and hybrid filtering techniques aim to capture structural changes in financial markets [8],[12]. Despite their effectiveness under certain conditions, these methods are computationally complex, require extensive parameter tuning, and may not be suitable for real-time trading applications. With the growth of computational power, machine learning techniques have also been applied to pairs trading. These include neural networks, reinforcement learning, and other data-driven models for pair selection and signal generation [14]. While such approaches can capture nonlinear relationships and complex patterns, they often suffer from overfitting, lack interpretability, and require large volumes of training data.

Overall, existing pairs trading approaches exhibit a clear trade-off between stability and adaptability. Static models fail to adjust to evolving market conditions, whereas dynamic models introduce noise and generate unstable trading signals [11], [12]. Advanced methods, although powerful, tend to increase computational complexity and reduce practical applicability. Moreover, most existing approaches rely on a single spread representation, either static or dynamic, which limits their ability to distinguish between genuine trading opportunities and noise-induced fluctuations [13].

To address these limitations, this study proposes a Dual Spread Confirmation Framework (DSCF) that integrates both static and dynamic spread representations. By combining long-term stability with short-term adaptability and executing trades only when both signals agree, the proposed approach enhances signal reliability, reduces noise, and improves overall trading performance.

III. PROPOSED APPROACH

The proposed DSCF is designed to enhance the robustness and reliability of traditional pairs trading strategies by integrating both static and dynamic spread representations. As illustrated in Fig. 1, the framework follows a structured architecture comprising data acquisition, preprocessing, parallel modeling, normalization, and a centralized decision-making module. Unlike conventional approaches that rely on a single spread, the DSCF employs a dual confirmation mechanism in which trading decisions are executed only when both long-term (static) and short-term (dynamic) signals indicate the same market condition. This coordinated signal validation process effectively filters noise, reduces false trading signals, and improves the overall consistency and performance of the strategy.

A. Static Spread Modeling (Long-Term Relationship)

The static spread model is designed to capture the long-term equilibrium relationship between two asset prices by estimating a constant hedge ratio using Ordinary Least Squares (OLS). This approach assumes that the relationship between the assets remains stable over time, thereby providing a reliable baseline for identifying deviations from equilibrium.

Let $P_1(t)$ and $P_2(t)$ denote the prices of the two assets at time t. The static model is expressed as:

$$P_1(t) = \alpha + \beta_{\text{static}} P_2(t) + \epsilon_t, \qquad (1)$$

where β_{static} represents the static hedge ratio and ϵ_t denotes the residual term. The static spread is computed as:

$$S_{\text{static}}(t) = P_1(t) - \beta_{\text{static}} P_2(t) \qquad (2)$$

This spread reflects the long-term deviation from equilibrium and provides a stable baseline for identifying mispricing opportunities.

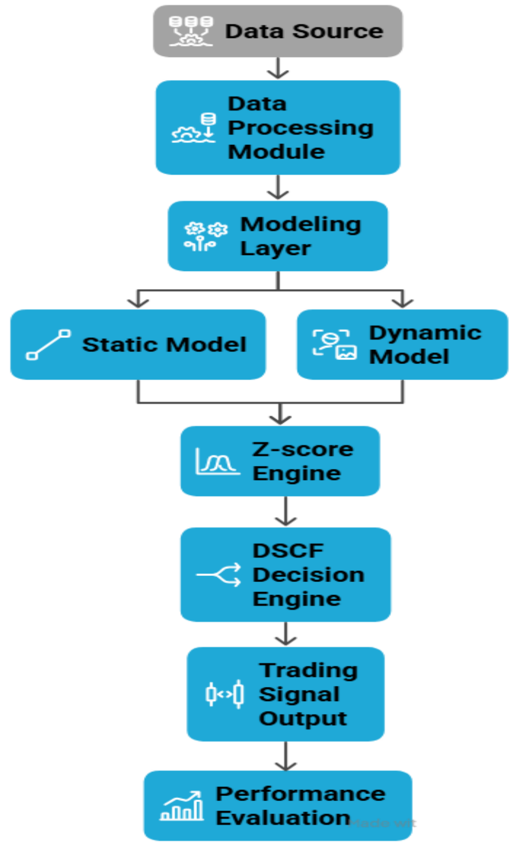

Fig. 1: Proposed Architecture of the DSCF

B. *Dynamic Spread Modeling (Short-Term Adaptation)*

To effectively capture time-varying relationships between asset prices, a rolling window regression framework is employed to estimate a dynamic hedge ratio. Unlike static models, this approach allows the hedge ratio to evolve over time, thereby adapting to short-term market fluctuations and structural changes in the relationship between the paired assets. At each time step, a dynamic hedge ratio β_t is re-estimated using the most recent window of observations, ensuring that the model reflects current market conditions. The dynamic model is defined as:

$$P_1(t) = \alpha_t + \beta_t P_2(t) + \epsilon_t \qquad (3)$$

The corresponding dynamic spread is given by:

$$S_{\text{dynamic}}(t) = P_1(t) - \beta_t P_2(t) \qquad (4)$$

This formulation enables the model to respond to changing market dynamics and improves the detection of short-term mispricing opportunities.

However, the increased sensitivity of the dynamic hedge ratio may introduce noise and instability in the spread, which can lead to frequent signal generation. This limitation motivates the need for a confirmation mechanism, as proposed in this study, to filter unreliable signals and enhance trading robustness.

C. Z-score Normalization

To standardize both spreads and enable consistent comparison, Z-score normalization is applied using rolling statistics. The normalized spreads are defined as:

$$Z_{\text{static}}(t) = \frac{S_{\text{static}}(t) - \mu_{\text{static}}(t)}{\sigma_{\text{static}}(t)} \quad (5)$$

$$Z_{\text{dynamic}}(t) = \frac{S_{\text{dynamic}}(t) - \mu_{\text{dynamic}}(t)}{\sigma_{\text{dynamic}}(t)} \quad (6)$$

where $\mu(t)$ and $\sigma(t)$ denote the rolling mean and standard deviation, respectively. The Z-score represents the number of standard deviations the spread deviates from its mean, allowing for standardized signal generation across time.

D. Dual Spread Confirmation Mechanism

The core contribution of the DSCF framework lies in its dual confirmation rule, where trading signals are generated only when both static and dynamic spreads indicate the same directional deviation. A buy signal is triggered when both normalized spreads indicate undervaluation, while a sell signal is generated when both indicate overvaluation. Formally, the trading rules are defined as:

$$\text{Buy Signal: } Z_{\text{static}}(t) < -\theta \quad \text{and} \quad Z_{\text{dynamic}}(t) < -\theta$$
$$\text{Sell Signal: } Z_{\text{static}}(t) > \theta \quad \text{and} \quad Z_{\text{dynamic}}(t) > \theta$$

Where θ is the predefined threshold, typically set to $\theta = 2$. This confirmation mechanism ensures that only high-confidence trading opportunities are executed, thereby reducing false positives and improving decision accuracy.

E. Position Management

The trading position is updated dynamically based on the generated signals. The position function is defined as:

$$\text{Position}(t) = \begin{cases} 1, & \text{if Buy Signal} \\ -1, & \text{if Sell Signal} \\ \text{Position}(t-1), & \text{otherwise} \end{cases}$$

This formulation ensures that positions are maintained until a new signal is generated, thereby reducing unnecessary trading activity and transaction costs.

F. Return Computation

The performance of the proposed strategy is evaluated based on the returns generated from the relative price movements of the paired assets. Instead of considering absolute returns, the strategy focuses on the spread between the returns of the two assets, which reflects the effectiveness of the pairs trading mechanism. The return at time t is computed using the position taken in the previous time step, ensuring realistic execution and avoiding look-ahead bias. The return function is defined as:

$$R(t) = \text{Position}(t-1) \cdot (r_1(t) - r_2(t))$$

Where $r_1(t)$ and $r_2(t)$ represent the returns of the respective assets. This formulation captures the profit generated from convergence in the spread.

The proposed DSCF framework effectively combines long-term stability with short-term adaptability by integrating static and dynamic spread representations. The dual confirmation mechanism plays a critical role in filtering noisy signals, thereby reducing false trading decisions. Empirical observations indicate that this approach significantly lowers trading frequency while improving risk-adjusted returns. Furthermore, the model maintains simplicity and computational efficiency compared to advanced machine learning or state-space models, making it suitable for practical implementation in real-world trading systems. The DSCF enhances pairs trading by introducing a robust signal validation mechanism that balances stability and adaptability while maintaining simplicity.

IV. RESULT AND DISCUSSION

The performance of the proposed DSCF is evaluated against traditional static and dynamic pairs trading strategies using historical price data obtained from the yfinance library. The dataset consists of daily closing prices of selected equity pairs over the period from 2018 to 2024. The analysis focuses on cumulative returns, trading signal behavior, and overall strategy stability to assess the effectiveness and robustness of the proposed approach. Fig. 2

presents the cumulative return comparison of the three strategies over the study period. It is observed that the proposed DSCF significantly outperforms both static and dynamic approaches. While the static strategy demonstrates moderate growth with noticeable fluctuations, the dynamic strategy exhibits weak performance with prolonged declining phases due to noisy and unstable signals. In contrast, the proposed DSCF shows a consistent upward trajectory, achieving the highest cumulative return. This demonstrates that the dual confirmation mechanism effectively filters weak signals and captures stronger mean-reversion opportunities.

Furthermore, the DSCF exhibits improved stability compared to the baseline methods. The static strategy shows several sharp drawdowns, reflecting its inability to adapt to evolving market conditions. The dynamic strategy, although adaptive, suffers from excessive volatility and frequent losses. In comparison, the DSCF maintains smoother growth with relatively controlled drawdowns, indicating enhanced risk management.

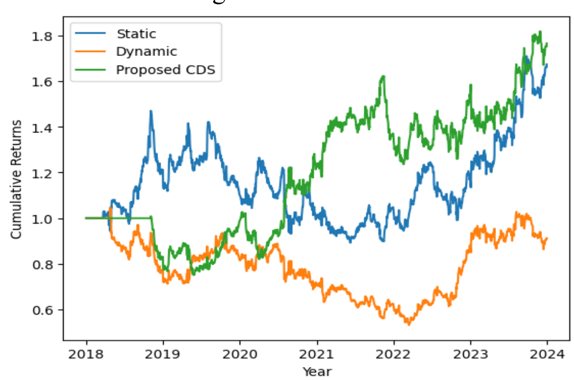

Fig. 2: Cumulative returns comparison of static, dynamic, and proposed DSCF Strategies

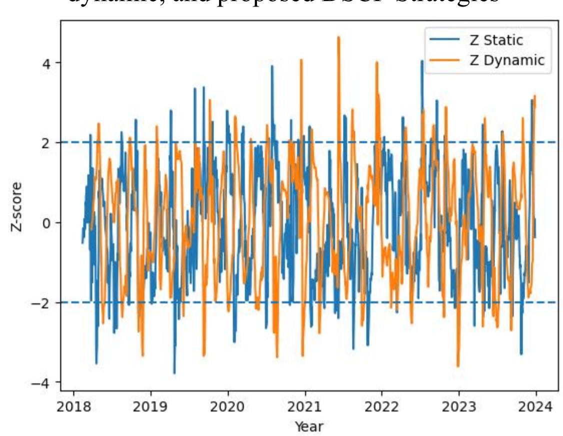

Fig. 3: Z-score Comparison of static and dynamic spreads

Fig. 3 illustrates the Z-score comparison of static and dynamic spreads. It can be observed that both Z-scores frequently cross the threshold levels, generating numerous potential trading signals. However, these signals often occur independently, leading to inconsistencies between the models. The DSCF framework addresses this limitation by executing trades only when both Z-scores simultaneously exceed the threshold in the same direction. This confirmation mechanism significantly reduces false signals and eliminates noise-driven trades.

The results highlight a clear trade-off between trading frequency and signal quality. The dynamic strategy generates frequent trades due to its sensitivity to short-term fluctuations, while the static strategy produces fewer but still relatively noisy signals. In contrast, the DSCF approach executes a limited number of trades with higher confidence, resulting in improved performance and lower transaction costs.

As summarized in Table I, the proposed DSCF achieves the highest Sharpe ratio, indicating superior risk-adjusted returns. It also records lower maximum drawdown compared to both static and dynamic strategies, reflecting better capital preservation. Furthermore, the reduced number of trades confirms minimized overtrading and enhanced signal efficiency.

Overall, the findings demonstrate that the DSCF framework effectively balances stability and adaptability by combining static and dynamic models. The dual confirmation mechanism improves signal reliability and ensures consistent trading performance by prioritizing signal quality over trading frequency.

Table 1: Performance Comparison of Pairs Trading Strategies

Strategy	Sharpe Ratio	Max Drawdown	Number of Trades
Static Strategy	0.5064	-0.3934	53
Dynamic Strategy	0.0363	-0.4920	61
Proposed DSCF	0.5709	-0.2554	11

V. CONCLUSION

This paper presents a structured and robust DSCF for pairs trading, supported by a clear processing pipeline and system architecture. The proposed approach systematically integrates data preprocessing, static and dynamic modeling, Z-score normalization, and a centralized dual-confirmation decision engine to generate reliable trading signals. By combining long-term equilibrium information from the static model with short-term adaptability from the dynamic model, the framework ensures that trades are executed only when both signals consistently indicate the same market condition. The experimental results demonstrate that the DSCF outperforms traditional static and dynamic strategies in terms of cumulative returns, risk-adjusted performance, and drawdown control. The architecture-driven design further contributes to reduced noise sensitivity and lower trading frequency, making the model both efficient and practical for real-world implementation. Overall, the proposed framework provides a balanced solution that enhances signal quality while maintaining simplicity and computational efficiency, thereby establishing a strong foundation for advanced pairs trading strategies.

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