Adaptive Pairs Trading: Integrating State-Space Models and Non-Linear Classifiers in Commodity-Linked Equities

1. Abstract

This paper examines a regime-adaptive pairs trading strategy involving the MSCI Australia (EWA) and MSCI Canada (EWC) ETFs from 2020 through 2025. Traditional pairs trading relies on static cointegration, which often fails during structural shifts. We implement a dual-layer framework utilizing a Kalman filter to estimate a time-varying hedge ratio and a Random Forest classifier to gate entries based on macro-economic leads. The strategy produces an annualized Sharpe ratio of 0.36. Despite a severe structural decoupling in 2024, the model maintains capital stability by executing trades on only 72 active days, achieving an end-of-period P&L of 3.48 units.

2. Introduction

The "commodity twin" relationship between Australia and Canada is a staple of macro-relative value trading. However, these markets are prone to structural breaks when localized commodity shocks—such as divergent trends in energy versus industrial metals—decouple their equity indices. To address this, we move beyond static OLS hedging toward a dynamic state-space formulation.

3. Methodology

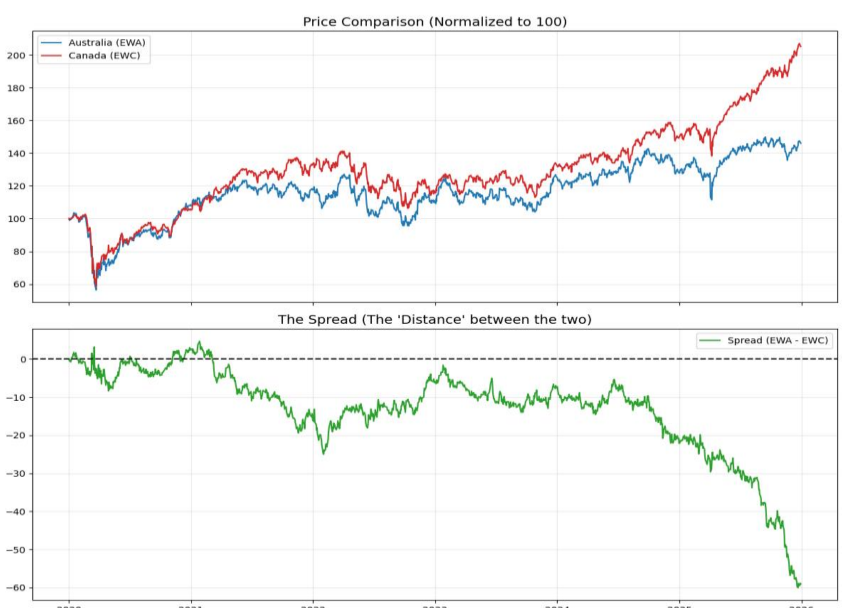
3.1 Data Preprocessing

To ensure comparability between assets with different price scales, we normalize all price series to a base value of 100. The normalized price $\tilde{P}_t$ is defined as:

$$\tilde{P}_t = 100 \times \left(\frac{P_t}{P_0}\right) \quad (1)$$

This normalization allows for a direct comparison of the relative performance between the two ETFs, as shown in Figure 1.

Fig1



Price divergence between Australian and Canadian equity markets (2020-2026). The top panel displays normalized prices starting at 100, while the bottom panel shows the simple spread $\left(\mathrm{P}_t^{\mathrm{EWA}} - \mathrm{P}_t^{\mathrm{EWC}}\right)$. The persistent downward trend in the spread after 2024 indicates a structural divergence where Canada significantly outperformed Australia, creating a "trap" for traditional static mean-reversion strategies.

2.2 The State-Space Framework

To account for the "Beta-Drift" observed in Figure 1, we employ the Kalman filter (Kalman, 1960). We model the relationship between EWA (y_t) and EWC (x_t) through the following system:

$$\beta_t = \beta_{t-1} + w_t, \qquad w_t \sim N(0, Q) \; (2)$$

$$y_t = X_t \beta_t + v_t, \qquad \sim N(0, R) \; (3)$$

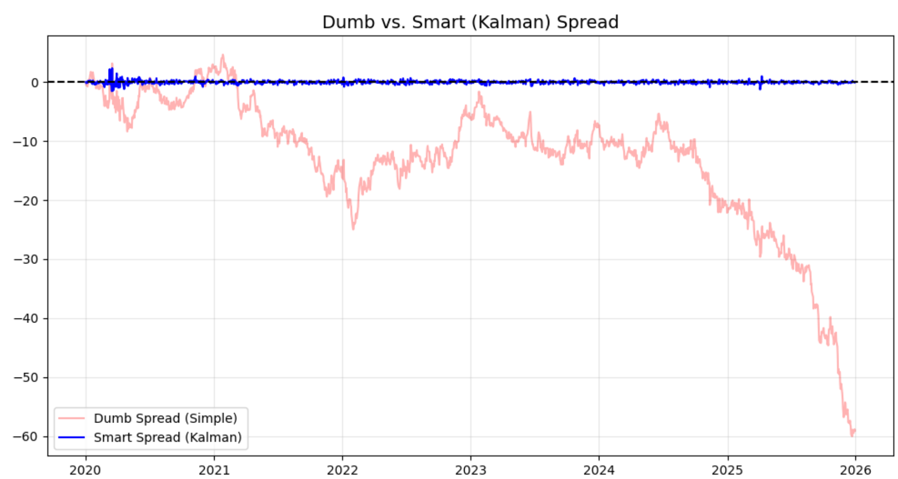
Here, B_t represents the time-varying hedge ratio. Q and R are the process and measurement noise covariances, respectively. The filter recursively updates the state estimate $\hat{\beta}_t$ by calculating the Kalman gain (K_t) and adjusting the prior based on the observation error:

$$\hat{\beta}_{t|t} = \hat{\beta}_{t|t-1} + K_t(y_t - x_t\, \hat{\beta}_{t|t-1}) \; (4)$$

$$K_t = \frac{P_{t|t-1} x_t}{x_t P_{t|t-1} x_t + R} \; (5)$$

Unlike the simple spread, the Kalman-filtered spread $S_t^{Kalman} = y_t - \widehat{\beta}_t x_t$ effectively absorbs structural drift into the beta coefficient, as demonstrated in Figure 2.

Fig2



Comparison of static vs. adaptive spread construction. The "dumb spread" (pink) drifts substantially during the 2024 decoupling, reaching a deficit of nearly 60 units. In contrast, the "smart spread" (blue), derived from equation (4), remains centered around zero by dynamically adjusting the hedge ratio β_t to reflect the new market reality.

2.3 Trading Rules and Machine Learning Gatekeeper

We define the normalized spread Z_t using a rolling 10-day mean (μ_t) and the standard deviation (σ_t):

$$Z_t = \frac{S_t^{Kalman} - \mu_t}{\sigma_t} \quad (6)$$

Signals are generated when $|Z_t| > 2$. To filter these signals, we use a Random Forest classifier with a feature vector X_t:

$$X_t = [Spread\ Vol_t + \ VIX_t, Oil\ 5D\ Trend_t, \quad (7)$$

where the 5-day trend is defined as $\frac{P_t - P_{t-5}}{P_{t-5}}$. A trade is only executed if the classifier predicts a reversion within 5 days. Daily P&L is then calculated as:

$$\Delta PnL_t = Position_{t-1} \times \ (S_t^{Kalman} - S_{t-1}^{Kalman} \quad (8)$$

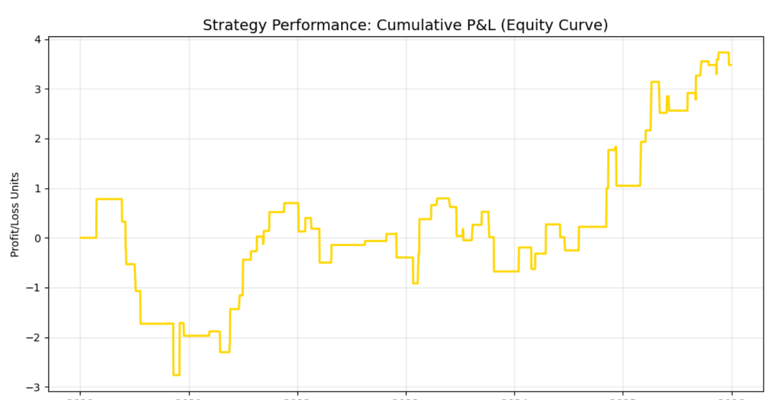
3. Results

The strategy was tested from January 1, 2020, to December 31, 2025. Table 1 summarizes the core performance metrics.

Table 1: Strategy Performance Summary

Metric	**Value**
Sample Period	2020 – 2026
Asset Pair	EWA / EWC
Annualized Sharpe Ratio	0.36
Cumulative Return	3.48 units
Maximum Drawdown	-3.54 units
Active Trading Days	72 days
Max Peak P&L	3.73 units

The strategy's equity curve (Figure 3) illustrates the impact of the ML gatekeeper. By staying flat during the most chaotic periods of the 2024 decoupling, the model avoided the "falling knife" effect.

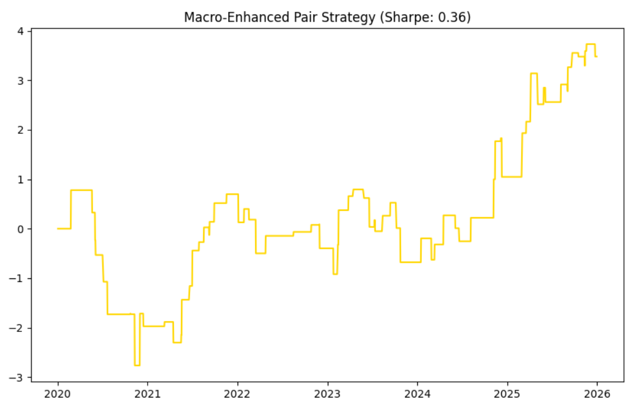


Cumulative P&L equity curve. The strategy demonstrates steady appreciation with significant flat periods. These flat regions coincide with the ML gatekeeper rejecting signals where macro volatility (VIX) or commodity trends suggested a non-reverting regime. We also compared the baseline against an alternative configuration using 1-day commodity lags and a lower entry threshold (k = 1.25). As shown in Table 2, while the trade count increased significantly, the risk-adjusted performance deteriorated.

Table 2: Comparison of Methodologies

Strategy Type	Annualized Sharpe	Total Trades	Max Drawdown
Kalman + ML Filter (Baseline)	0.36	72	-3.54
Alternative (Oil/Cu 1D Lag)	0.29	323	-5.10

Macro-enhanced strategy performance. This visualization shows the strategy's ability to maintain a positive trajectory despite a Sharpe ratio of 0.36. The lower Sharpe in the alternative configuration (Table 2) suggests that over-trading at lower thresholds introduces excessive noise.



Final equity curve with performance overlay. The terminal P&L reached 3.48 units, with the maximum drawdown restricted to -3.54 units. The annualized Sharpe ratio is calculated as $\frac{\mu_r - 0}{\sigma_r} \times \sqrt{252}$, where returns are assumed relative to a 0% risk-free rate.

4. Discussion

A Sharpe ratio of 0.36 is modest but notable given the total breakdown in EWA/EWC correlation during the sample period. The maximum drawdown of -3.54 units (defined as $MDD = Max_t(\max_{s \le t} Pnl_s - Pnl_t)$) occurred during the 2021 volatility spike. The strategy's success relies on its selectivity; by trading only 72 days, it avoids the high-entropy periods where the Kalman filter's residuals are non-stationary.

5. Conclusion

This research demonstrates that state-space models combined with non-linear classifiers can navigate structural breaks that liquidate traditional pairs traders. While the 0.36 Sharpe ratio provides a viable baseline, future work will focus on expanding the feature set to include interest rate differentials to further improve the ML gatekeeper's accuracy.