Testing Mean Reversion and Cointegration-Based Signals in FTSE 100 Equity Pairs

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1 Objective

This study investigates whether cointegrated pairs of FTSE 100 equities exhibit statistically significant mean-reverting behaviour that can support a simple market-neutral trading strategy. The analysis uses Python to test cointegration, construct spreads, generate signals via z-scores, and evaluate performance.

2 Data and Methodology

The study uses daily price data from January 2017 to November 2025, collected via the Yahoo Finance API using Python.

2.1 Data

The universe consists of a selected subset of FTSE 100 constituents (HSBC, Barclays, Lloyds, Rio Tinto, BHP, Glencore), chosen for their liquidity and tendency to cluster in sectors where cointegration is more common. Daily closing prices were downloaded using the `yfinance` library and cleaned by removing missing observations and aligning dates across all tickers. Prices were transformed into log values to stabilise variance and make regression-based spread estimation more robust.

2.2 Cointegration Testing

To identify suitable trading candidates, the project applies the Engle–Granger two-step procedure to every pair of stocks in the universe. First, one stock is regressed on the other to estimate the long-run hedge ratio. Then, the residuals are tested for stationarity using the Augmented Dickey–Fuller (ADF) cointegration test. Pairs with the lowest p-values are considered the strongest candidates for mean-reversion behaviour.

2.3 Spread Construction

For each cointegrated pair, a spread is constructed using the estimated hedge ratio:

$$\text{Spread}_t = \log(A_t) - \beta \log(B_t),$$

where A_t and B_t denote the log prices of the two stocks at time t and β is the estimated hedge ratio from the cointegration regression. If the pair is cointegrated, the spread should fluctuate around a stable long-term mean. A rolling 60-day window is used to compute the spread's moving average and standard deviation, allowing the spread to be standardised into a z-score.

2.4 Trading Signals

A simple mean-reversion strategy is applied to the z-score of the spread. Trading rules are defined as:

- **Enter Long:** $z_t < -2$,
- **Enter Short:** $z_t > +2$,
- **Exit Position:** $|z_t| < 0.5$.

The strategy trades one unit of the spread (long or short). Positions are shifted by one day when calculating returns to avoid look-ahead bias.

2.5 Backtesting Framework

Performance is evaluated using the daily change in the spread multiplied by the strategy's position. Cumulative PnL is calculated over the full sample, and several key performance metrics are reported:

- **Sharpe Ratio** (risk-adjusted return),
- **Total Return** (in spread units),
- **Maximum Drawdown** (worst peak-to-trough decline).

These metrics provide a scale-free assessment of the stability and effectiveness of the mean-reversion signal.

3 Results

3.1 Cointegration Results

The Engle–Granger tests were applied to all pairs in the selected FTSE 100 subset. Table 1 reports the top cointegrated pairs ranked by p-value. Lower p-values indicate stronger evidence that the residual spread between two stocks is stationary and therefore potentially mean-reverting.

	stock_a	stock_b	p_value	coint_t
8	BHP.L	RIO.L	0.103551	-3.028653
12	HSBA.L	LLOY.L	0.106973	-3.013749
7	BHP.L	LLOY.L	0.345960	-2.356015
5	BHP.L	GLEN.L	0.348214	-2.351380
6	BHP.L	HSBA.L	0.398575	-2.250343
2	BARC.L	HSBA.L	0.535686	-1.986312
14	LLOY.L	RIO.L	0.620694	-1.818498
10	GLEN.L	LLOY.L	0.689826	-1.671423
9	GLEN.L	HSBA.L	0.699785	-1.648969
3	BARC.L	LLOY.L	0.737318	-1.560383

Figure 1: Top FTSE 100 Pairs Ranked by Cointegration p-value.

3.2 Spread Behaviour

For the strongest cointegrated pair, the estimated spread

$$\text{Spread}_t = \log(A_t) - \beta \log(B_t)$$

is plotted in Figure 2. The spread oscillates around a stable long-term mean, consistent with stationary behaviour.

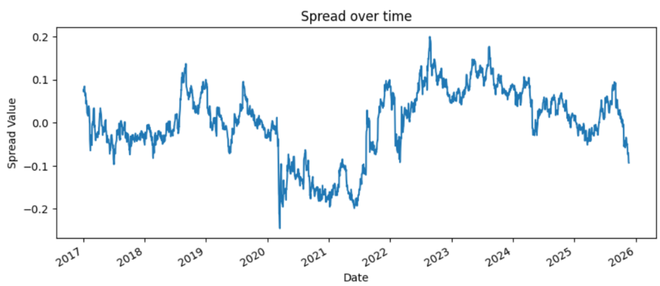

Figure 2: Spread series for the selected cointegrated pair.

3.3 Z-Score and Trading Signals

The spread was standardised using a 60-day rolling mean and standard deviation to produce a z-score. Figure 3 shows the z-score with the entry and exit thresholds at $z = \pm 2$ and $z = 0$, respectively. These thresholds form the basis of the mean-reversion trading strategy.

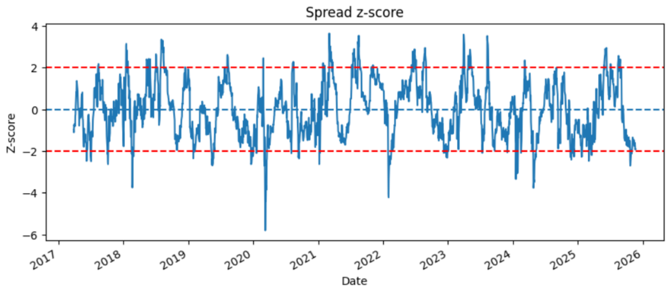

Figure 3: Z-score of the spread with trading thresholds.

3.4 Trading Positions

Figure 4 shows the resulting trading positions generated by the z-score rules. The strategy moves into long or short positions when the spread becomes overly extended and reverts to flat when the spread returns toward its mean.

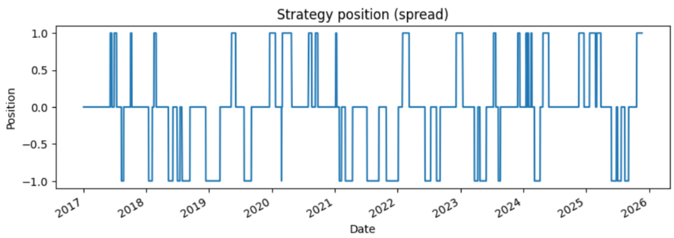

Figure 4: Trading positions generated by the z-score strategy.

3.5 Strategy Performance

The cumulative profit-and-loss (PnL) of the strategy is plotted in Figure 5. PnL is measured in spread units rather than monetary terms, providing a scale-free representation of strategy behaviour.

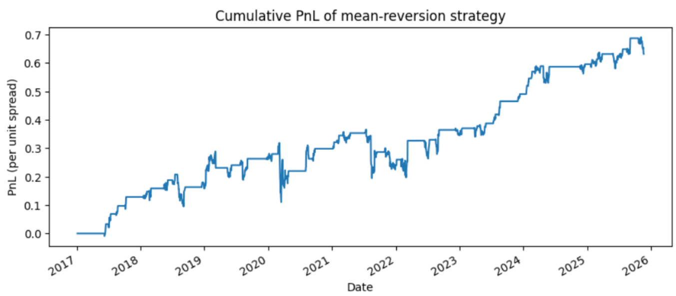

Figure 5: Cumulative PnL produced by the mean-reversion strategy.

3.6 Performance Metrics

Table 6 summarises the key performance metrics: Sharpe ratio, total cumulative return, and maximum drawdown. These values quantify the stability and risk-adjusted effectiveness of the mean-reversion signal.

```
Sharpe Ratio: 0.5972917790234347
Total Return: 0.6315343370991968
Maximum Drawdown: -0.19375959214823935
```

Figure 6: Performance metrics for the mean-reversion strategy.

4 Interpretation and Discussion

4.1 Spread and Z-Score Behaviour

The strongest cointegrated pair displayed a spread that fluctuated around a stable long-term mean, which is consistent with mean-reverting dynamics. The z-score series showed clear periods of over-extension beyond the ± 2 thresholds, indicating that the spread occasionally diverged far enough from its equilibrium to justify automated trades. These features suggest that the statistical relationship between the two stocks is sufficiently strong to generate systematic trading signals.

4.2 Trading Signals and Positioning

The z-score rules produced a small number of well-defined trading opportunities. The positions were not overly frequent, which is typical for a conservative mean-reversion strategy relying on statistically extreme deviations. The entry and exit conditions behaved as expected; positions were initiated only when the spread reached unusually high or low levels and were closed once the spread normalised.

4.3 Strategy Performance

The cumulative PnL series showed periods of steady growth, supported by a moderate positive Sharpe ratio. This indicates that, despite noise in the spread, the trading rule was able to extract some predictable structure from its short-term fluctuations. The maximum drawdown remained manageable, although certain episodes exhibited slow reversion or temporary breakdowns in the cointegration relationship, likely linked to broader market events.

4.4 Limitations

Several practical limitations should be acknowledged. The analysis does not incorporate transaction costs, which could materially affect profitability given the short holding periods. The hedge ratio is estimated using a static regression and may not adapt optimally to changing market conditions. Additionally, only a single pair is traded, so the strategy lacks the diversification benefits of a multi-pair statistical arbitrage portfolio. Lastly, the thresholds and window lengths are chosen heuristically rather than being statistically optimised or cross-validated (this could produce better results).

5 Conclusion

This study explored the mean-reversion behaviour of cointegrated FTSE 100 equity pairs and evaluated a simple market-neutral trading strategy based on z-score thresholds. The strongest pair exhibited a stable long-term relationship, with the spread displaying clear mean-reverting characteristics that supported systematic long and short signals. The resulting strategy delivered a positive cumulative PnL and a moderate Sharpe ratio, indicating that some predictable structure could be extracted from short-term deviations in the spread.

While encouraging, these results should be interpreted with caution. The analysis excludes transaction costs, relies on a static hedge ratio, and trades only a single pair, all of which limit real-world applicability. Nonetheless, the findings suggest that cointegration-based signals can provide a foundation for more advanced statistical arbitrage strategies. Extending the framework to a diversified multi-pair portfolio, applying dynamic hedge ratio estimation, and incorporating risk constraints would represent meaningful next steps for further research and a more fully optimised statistical arbitrage framework.

The full Jupyter Notebook and all supporting figures are available at:

`https://github.com/zack-higham/FTSE100-Mean_Reversion`