Kalman Filter-Based Statistical Arbitrage: A Dynamic Pairs Trading Strategy

Chong Tin Tak

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The Hong Kong University of Science and Technology

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Introduction: The Quest for Market Neutrality

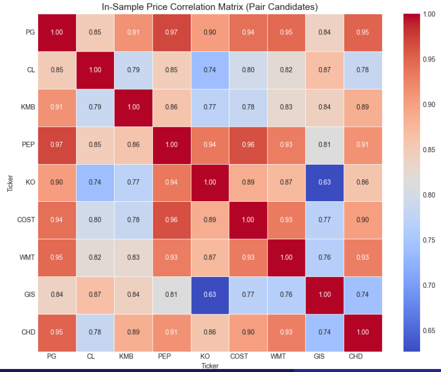
- **Goal:** Develop & evaluate a dynamic, market-neutral pairs trading strategy.
- **Why Pairs Trading?**
  - Exploit temporary price divergences between related assets (cointegration).
  - Aim for reduced dependence on market direction.
- **The Challenge:**
  - Asset relationships aren't static – they drift!
  - Static OLS models fail to adapt $\rightarrow$ Risk exposure.
- **Our Solution: The Kalman Filter**
  - Dynamically estimates changing relationships (hedge ratio β, intercept α) in real-time.
  - Leads to a more **adaptive** & **robust** strategy.
- **Example Pair:** CL (Colgate) vs GIS (General Mills) [Consumer Staples]

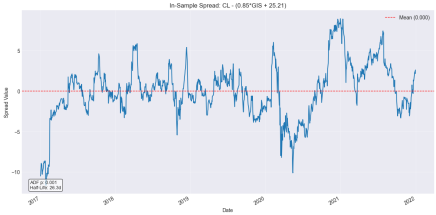
Methodology: Finding the Right Pair (CL & GIS)

Rigorous Selection Process (In-Sample: 2017-2021):

1. Screened Consumer Staples sector stocks.
2. Tested pairs using Engle-Granger ($p < 0.05$).
3. Confirmed spread stationarity with ADF test ($p < 0.05$).
4. Checked Half-Life (CL/GIS: 26.3 days - viable range).

Visual Diagnostics (In-Sample):

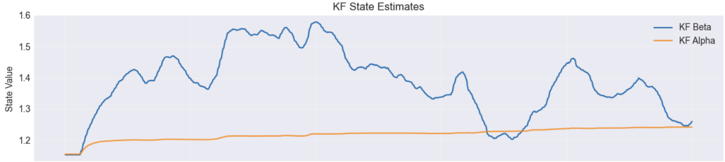




Methodology: Dynamic Hedging & Trading Logic

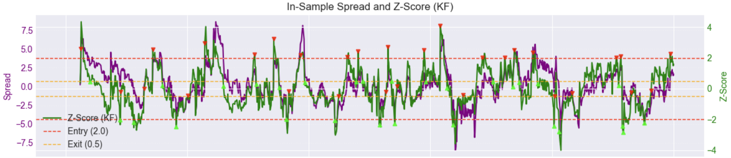
Kalman Filter in Action:

- Models: Spread $= CL_t - (\beta_t \times GIS_t + \alpha_t)$
- Estimates time-varying β_t (hedge) & α_t (level).



Trading Signal: Z-Score of dynamic KF Spread

- Z = (Spread - Roll Mean) / Roll Std Dev (60d Window)
- Trade Rules: Enter @ +/- 2.0 Z — Exit @ +/- 0.5 Z



Results: Out-of-Sample Performance (2022-2024)

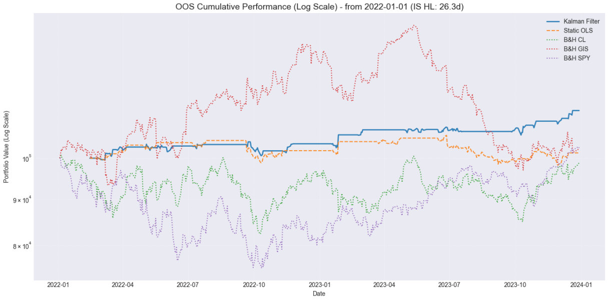
The Real Test: Performance on unseen data.

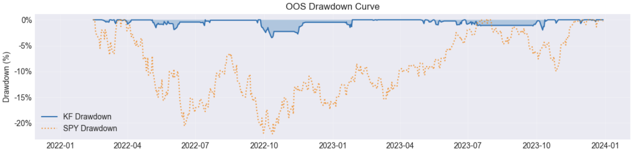
Strategy	CAGR	Ann. Vol.	Sharpe	Max DD	Calmar	Trades
Kalman Filter	**0.067**	**0.053**	**1.259**	**-0.035**	**1.938**	**36**
Bench: SPY	0.013	0.195	0.165	-0.245	0.054	0
Bench: CL	-0.005	0.184	0.065	-0.182	-0.028	0
Bench: GIS	0.014	0.205	0.168	-0.309	0.044	0
Bench: Static OLS	0.007	0.061	0.147	-0.073	0.099	20

Key Highlights:

- **Excellent Risk-Adjusted Return:**
  KF Sharpe (**1.26**) vs SPY (0.17) & Static OLS (0.15)
- **Superior Risk Control:**
  KF Max Drawdown (**-3.5%**) vs SPY (-24.5%)!
- **KF Advantage:** Dynamic approach significantly outperforms static model & benchmarks OOS.

Results: Visual Evidence (Out-of-Sample)

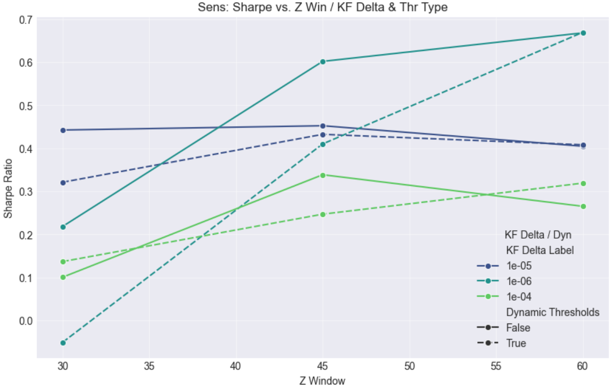




Message: Strategy delivers consistent returns while effectively managing risk.

Parameter Validation:

- Sensitivity analysis performed across key params (Window, Delta, Thresholds, Dynamic Mode).
- Optimal parameters (W=60, $\Delta = 1e - 06$, E=2.0, X=0.5) identified and used for final OOS results.



Conclusion: Why Use This Kalman Filter Approach?

Summary: Successfully implemented & validated a dynamic KF pairs trading strategy with strong OOS results.

Key Advantages Demonstrated:

- ✓ **Adaptability:** Tracks changing relationships where static models fail.
- ✓ **Risk Control:** Low volatility & minimal drawdown (**-3.5%**).
- ✓ **Performance:** Superior risk-adjusted returns (Sharpe **1.26**) vs benchmarks & static models.
- ✓ **Systematic:** Data-driven selection & tuning.

Value Proposition: This KF methodology offers a **robust framework** for statistical arbitrage, aiming for consistent, market-neutral returns with **controlled risk**.

- Thank You -