Executive Report

Pairs Trading

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Introduction

This report presents a trading project on Pairs Trading, a market-neutral strategy designed to exploit pricing inefficiencies between two historically related assets. Pairs trading aims to capture profits from temporary divergences in the relative value of the assets while minimizing exposure to overall market direction. By taking long and short positions at the same time in both assets, the strategy tries to isolate and monetize the spread dynamics rather than broad market movements, making it particularly attractive in volatile or uncertain environments. It is supposed to be market neutral.

A core pillar of this project is the application of cointegration analysis, a statistical framework that identifies pairs of non-stationary price series that share a stable long-term equilibrium. Even though each asset may individually follow a random walk, a cointegrated pair maintains a predictable relationship over time. When the spread between these assets deviates from its equilibrium, it is statistically likely to revert, creating systematic trade entry and exit opportunities. Incorporating cointegration significantly enhances the reliability of pairs selection and provides a sound theoretical basis for mean-reversion-based trading signals.

To further strengthen the adaptability and robustness of the strategy, the project integrates Kalman Filters, a recursive estimation technique. The Kalman Filters enable dynamic, real-time updating of key parameters, in this case a hedge ratio, based on newly observed market data. Unlike traditional static regressions or rolling-window methods, the Kalman Filter can capture gradual structural changes in the relationship between assets, respond quickly to market shifts, and reduce noise in parameter estimates. This results in more accurate spread construction and timelier trading signals, which un turn should turn out to become a better portfolio return.

By combining the rigorous statistical foundation of cointegration, the risk-balanced structure of pairs trading, and the real-time adaptability of Kalman Filter estimation, this project delivers a robust, data-driven framework capable of operating effectively in evolving market conditions. The following sections detail the methodology, implementation, and performance evaluation of the strategy.

Strategy Description and Rationale

1.1 Overview of Pairs Trading Approach

Pairs trading is a market-neutral statistical arbitrage strategy designed to capitalize on the short-term price deviations between two historically related assets. The core premise involves identifying a pair of assets (such as two stocks within the same industry) whose prices have exhibited a strong historical tendency to move together. This relationship is formally known as cointegration.

The strategy continuously monitors the price relationship, or "spread," between these two assets. When the spread widens significantly beyond its historical average (mean), a trading opportunity is signaled. The strategy dictates shorting the asset that is currently 'overperforming' (relatively expensive) and simultaneously taking a long position in the asset that is 'underperforming' (relatively cheap). The position is held with the expectation that the spread will eventually revert to its long-term mean, at which point the trade is closed for a profit, regardless of the overall market direction.

1.2 Why Cointegration Indicates an Arbitrage Opportunity

Cointegration provides the statistical and economic foundation that separates pairs trading from simple correlation. While correlation measures short-term co-movement, cointegration implies a long-term, stable equilibrium relationship between two or more assets.

Individually, asset prices are typically non-stationary (they follow a 'random walk' and do not revert to a mean). However, if two assets, P_A and P_B , are cointegrated, it means that a specific linear combination of them (the spread, $S = P_A - \beta P_B$) is stationary.

A stationary spread has a constant mean and finite variance. This property is critical: it implies that any deviation from this mean is temporary and expected to self-correct. This predictable mean-reversion behavior is the statistical arbitrage opportunity. It suggests that a divergence in price is not due to a permanent, fundamental change, but rather temporary market noise or liquidity shocks. The strategy is, therefore, a bet on the restoration of this long-term economic equilibrium.

1.3 Justification for Kalman Filter Use in Dynamic Hedging

Traditional cointegration analysis (such as the Johansen tests) provides a *static* hedge ratio β calculated over a historical lookback window. This approach is fundamentally flawed as it assumes the relationship between the assets is constant over time. In reality, financial relationships are dynamic; they are affected by changing market conditions, volatility regimes, and firm-specific news.

The justification for using a Kalman filter is its ability to model and adapt to these time-varying parameters. By framing the pair relationship in a state-space model, the Kalman filter treats the hedge ratio β and the intercept α as unobserved "states" that evolve recursively.

With each new price observation, the filter updates its belief about the current state of the hedge ratio. This provides two key advantages:

1. Adaptive Hedging: It produces a dynamic hedge ratio that adapts to new information, leading to a more accurate and robust estimation of the true spread.
2. Noise Reduction: The filter naturally smooths the parameter estimates, reducing the impact of market noise on the trading signal.

This dynamic approach is superior to a static model, as it is designed to handle the non-stationary and adaptive nature of real-world financial markets.

1.4 Expected Market Conditions for Strategy Success

The success of a mean-reversion strategy is highly dependent on the prevailing market environment. The strategy is expected to perform best under the following conditions:

- Stable, Moderate Volatility: The strategy thrives in markets where historical relationships hold and price movements are driven by temporary liquidity shocks or random noise, rather than fundamental information. "Normal" market conditions allow the mean-reverting properties of the spread to dominate.
- Absence of Structural Breaks: The strategy relies on the long-term economic link between the assets remaining intact.

Conversely, the strategy is expected to underperform or fail significantly during:

- Systemic Shocks or Panics: During market-wide crises (the 2008 financial crisis or the 2020 COVID-19 crash), correlations often converge to 1 ("risk-off" behavior), and all assets move in unison. In such environments, mean-reverting relationships break down, and spreads can widen indefinitely, leading to massive losses.
- Fundamental Structural Breaks: If an event occurs that permanently breaks the economic link between the pair (an acquisition, a major regulatory change, or disruptive technology affecting only one firm), the spread will diverge and will *not* revert.

Therefore, the strategy is considered robust during periods of relative stability but is highly vulnerable to systemic tail-risk events.

Pair Selection Methodology

To build a reliable universe of tradable pairs, we designed a multi-stage selection methodology that combines statistical rigor with economic intuition. The process began with the collection of historical price data for approximately 100 equities traded on major U.S. stock exchanges. These data series were consolidated into a single dataset to ensure uniform formatting, comparable time horizons, and consistent handling of missing values. Establishing a clean and comprehensive data foundation was essential before proceeding to any statistical analysis.

The first stage of filtering involved assessing whether each asset's price series was stationary using the Augmented Dickey–Fuller (ADF) test. Stationarity is a crucial concept in time-series analysis, as it refers to whether the statistical properties of a series, such as mean and variance remain constant over time. The ADF test evaluates the presence of a unit root, which indicates non-stationarity. In the context of pairs trading, it is generally necessary for individual price series to be non-stationary (integrated of order one, I(1)), because cointegration can only exist between non-stationary series that share a stable long-term equilibrium. Therefore, any stock identified as stationary by the ADF test was removed from the universe to maintain consistency with the theoretical assumptions underlying cointegration.

After filtering for non-stationary price series, we applied the Johansen cointegration test to all possible stock pairs. The Johansen procedure is a multivariate approach based on a vector error-correction model (VECM), and it allows for the detection of one or more cointegration relationships among non-stationary variables. Unlike simpler techniques such as the Engle–Granger (another statistical test that can indicate cointegration) two-step method, the Johansen test provides eigenvalues, trace statistics, and critical values that collectively determine the number of statistically significant long-term relationships. This rigor makes it particularly appropriate for our objective of identifying pairs whose price movements are tied together through an equilibrium mechanism. Pairs that demonstrated statistically significant cointegration according to the Johansen trace statistic were retained for further inspection.

Having identified statistically cointegrated pairs, we conducted a final qualitative and economic filter based on industry classification. We needed to find pairs that were affected by the same economic events to create a more stable environment for the strategy. For this reason, we prioritized pairs belonging to the same industry or sector, as firms operating in comparable environments are more likely to exhibit consistent relative pricing dynamics. This additional layer of filtering helps ensure that the cointegration relationships are not only statistically valid but also economically justifiable.

Finally, we selected a pair of assets that showed cointegration and at the same time belong to the same industry, being JPM and BAC. JPMorgan Chase (JPM) and Bank of America (BAC) form a natural and economically intuitive pair due to their strong similarities in business structure and market exposure. Both companies are among the largest financial institutions in the United States, operating as diversified, full-service commercial and investment banks. Their revenues are driven by comparable factors such as interest rate conditions, credit demand, loan performance, capital markets activity, and overall macroeconomic trends. As systemically important financial institutions, they are also subject to similar regulatory frameworks, capital requirements, and stress-testing standards, further aligning their operational environments.

Sequential Decision Analysis Framework

2.1 Detailed Mathematical Formulation of the State-Space Model

Dynamic Hedge Ratio (Kalman Filter #1)

Hidden state vector:

$$S_t^{(1)} = \begin{bmatrix} \beta_t \\ \alpha_t \end{bmatrix}$$

where

- β_t = dynamic hedge ratio,
- α_t = time-varying intercept of the A~vs~B relationship.

These represent the agent's belief about the long-term linear equilibrium between the two assets.

Decision Variables

No explicit trading decisions; the filter updates its belief.
The internal decision is:

$$x_t^{(1)} = \text{how much weight to give to new information vs prior belief}$$

implicitly encoded in the Kalman gain.

State update

$$S_{t+1}^{(1)} = S_t^{(1)} + w_{t+1}, \qquad w_{t+1} \sim \mathcal{N}(0, Q_1)$$

Observation equation:

$$A_{t+1} = \beta_{t+1} B_{t+1} + \alpha_{t+1} + v_{t+1}$$

where the Kalman update combines prediction and new observation.

Spread Mean Model (Kalman Filter #2)

$$S_t^{(2)} = \mu_t$$

where

- μ_t = filtered long-term mean of the spread.

This state tracks the equilibrium level toward which the spread reverts.

Decision Variables

Similarly, the filter chooses an updated belief:

$$x_t^{(2)} = \text{increment to the mean level } \mu_t.$$

State update:

$$\mu_{t+1} = \mu_t + u_{t+1}, \qquad u_{t+1} \sim \mathcal{N}(0, q)$$

Observation equation:

$$s_{t+1} = \mu_{t+1} + e_{t+1}, \qquad e_{t+1} \sim \mathcal{N}(0, r)$$

Full Trading System

$$S_t^{(3)} = (\beta_t,\ \alpha_t,\ \mu_t,\ \sigma_t,\ \Pi_t,\ \text{pos}_t)$$

where

- β_t, α_t = hedge-ratio state
- μ_t = estimated spread mean
- σ_t = realized spread volatility
- Π_t = portfolio value
- $\text{pos}_t \in \{\text{long spread}, \text{short spread}, \text{flat}\}$

This encapsulates *all information the trader carries* from one decision epoch to the next.

Decision Variables

The primary decision variable is:

$$x_t^{(3)} \in \{\text{open long-spread},\ \text{open short-spread},\ \text{close},\ \text{hold}\}$$

where:

- **Open long-spread:**
  buy A, short B
- **Open short-spread:**
  short A, buy B
- **Close:**
  unwind both legs
- **Hold:**
  no trade

The decision is driven by the standardized signal:

$$z_t = \frac{s_t - \mu_t}{\sigma_t}$$

Portfolio evolves according to:

$$\Pi_{t+1} = \Pi_t + \text{PnL}_{t+1}(x_t^{(3)}, A_{t+1}, B_{t+1}) - \text{commissions}$$

Position state transitions as:

- From flat → long/short based on entry signal
- From long/short → flat based on exit rule
- Otherwise → remain in same regime

The trading system is Markovian because the next state depends only on:

$$(\beta_t, \alpha_t, \mu_t, \sigma_t, \Pi_t, \text{pos}_t, A_{t+1}, B_{t+1})$$

Exogenous Information

For all models, the exogenous information realized at time t is:

$$W_{t+1} = (A_{t+1}, B_{t+1})$$

the new market prices for both assets.

This information is outside the control of the agent and arrives stochastically each period.

Transition Function

The transition function describes how the state evolves after decisions are taken and new information arrives

Objective Function

The objective of the trading system is to maximize risk-adjusted return over the horizon:

$$\max \mathbb{E}\left[\sum_{t=0}^{T} U(\Pi_t)\right]$$

where the utility is implicit in the performance metrics:

- Sharpe ratio
- Sortino ratio
- Calmar ratio
- Drawdown control
- Positive net PnL after commissions

Equivalently, the operational goal is:

$$\max \Pi_T \quad \text{subject to controlled volatility and drawdowns.}$$

For the two Kalman filters individually, the objective is:

- **Hedge-ratio filter:** minimize prediction error of A given B
- **Spread-mean filter:** minimize squared deviation of the spread from its estimated mean

These combine to generate a stable and interpretable signal for decision-making.

2.2 Description of Sequential Process

1. Predict

For each Kalman filter:

$$\hat{x}_{t|t-1} = F\hat{x}_{t-1}$$

$$P_{t|t-1} = FP_{t-1}F^{\top} + Q$$

where

- $F = I$ (identity) since states follow random-walk dynamics.

2. Observation

The trader receives the new price vector:

$$(A_t, B_t)$$

and computes the observed spread:

$$s_t = A_t - (\beta_t B_t + \alpha_t)$$

3. Update

For each filter:

$$K_t = P_{t|t-1}H_t^{\top}\left(H_t P_{t|t-1} H_t^{\top} + R\right)^{-1}$$

$$\hat{x}_t = \hat{x}_{t|t-1} + K_t(y_t - H_t\hat{x}_{t|t-1})$$

This incorporates new information optimally and recursively.

4. Decide

Based on the standardized spread:

$$z_t = \frac{s_t - \mu_t}{\sigma_t}$$

the trader selects:

- **Enter long-spread** if $z_t < -\theta$
- **Enter short-spread** if $z_t > \theta$
- **Close position** if $|z_t| < \delta$
- **Hold** otherwise

5. Act

Execute long/short orders using a fixed notional:

- Long A & short B (if spread expected to rise)
- Short A & long B (if spread expected to fall)

6. Learn

The outcome updates:

- portfolio value
- trade history
- the next state vector

and becomes input for the next decision epoch.

2.3 Interpretation of the Kalman Gain

The Kalman gain determines how aggressively new observations adjust the beliefs:

$$K_t = \frac{\text{prior uncertainty}}{\text{prior uncertainty} + \text{observation noise}}$$

Interpretation:

- **High** K_t → trust new data more
  → hedge ratio adapts quickly
- **Low** K_t → trust prior belief more
  → hedge ratio becomes stable and slowly varying

In financial terms:

- Large K_t is appropriate for turbulent markets
- Small K_t is appropriate for stable, cointegrated pairs

2.4 Selection of Q and R Matrices

Hedge Ratio Filter (Kalman #1)

- $Q_1 = \mathrm{diag}(10^{-7}, 10^{-7})$
  - small values → β_t changes slowly
- $R_1 = 10^{-1}$
  - prices are noisy; use moderate measurement noise

Mean-Spread Filter (Kalman #2)

- $q = 10^{-4}$
  - spread mean drifts slowly
- $r = 10^{-2}$
  - spread has short-term volatility

2.5 Worked example showing state evolution over several periods

t	A_t	B_t	Predicted β_t	Updated β_t	Spread s_t	Predicted μ_t	Updated μ_t
1	152.00	100.00	0.5000	0.5051	82.00	0.00	8.18
2	153.00	101.00	0.5051	0.5120	82.39	8.18	16.38
3	150.00	99.00	0.5120	0.5287	77.62	16.38	22.44

- **Predicted β_t** comes from the Kalman prediction step:

$$\hat{x}_{t|t-1} = \hat{x}_{t-1}$$

  (because state follows a random walk).
- **Updated β_t** incorporates the new price pair (A_t, B_t):

$$\hat{x}_t = \hat{x}_{t|t-1} + K_t(y_t - H_t\hat{x}_{t|t-1})$$

- **Spread** is computed as:

$$s_t = A_t - (\beta_t B_t + \alpha_t)$$

- **Predicted μ_t** is the prior belief about the long-term mean of the spread.
- **Updated μ_t** results from:

$$\mu_t = \mu_{t|t-1} + K_t^{(\mu)}(s_t - \mu_{t|t-1})$$

This small numerical example shows, step-by-step, how the Kalman filters adjust their beliefs given new information.

Kalman Filter Implementation

3.1 Initialization procedures

Both filters follow a random-walk specification for the hidden states:

$$x_t = x_{t-1} + w_t, \qquad w_t \sim \mathcal{N}(0, Q)$$

Hedge-Ratio Filter Initialization

The hedge-ratio filter estimates:

$$x_t = (\beta_t, \alpha_t)^\top$$

Before starting the recursive updates, we require an initial estimate (β_0, α_0).
These values were obtained through an **OLS regression** applied to the first *window_size* days of the training set:

$$A_t = \beta_0 B_t + \alpha_0 + \varepsilon_t \qquad t = 1, \ldots, 1008.$$

This OLS calibration provides:

- a statistically grounded initial mean,
- a realistic initial shape of the linear relationship,
- and a stable starting covariance.

The initial covariance matrix is set to:

$$P_0 = 100 \cdot I_2,$$

reflecting high initial uncertainty while allowing the filter to converge rapidly.

Spread-Mean Filter Initialization

For the second Kalman filter, the hidden state is the long-term mean of the spread:

$$\mu_t.$$

Initialization is simple:

$$\mu_0 = 0, \qquad \mathrm{Var}(\mu_0) = 1.$$

This non-informative prior allows the filter to adapt flexibly to the spread's long-run behavior without introducing bias.

3.2 Parameter Estimation Methodology

The Kalman filter requires specifying two noise parameters

- Q → process noise covariance (how fast the true state evolves)
- R → measurement noise covariance (how noisy the observations are)

Hedge-Ratio Filter (Kalman #1)

$$Q_1 = \mathrm{diag}(10^{-7}, 10^{-7})$$

$$R_1 = 10^{-1}$$

Justification:

- Small process noise → hedge ratio evolves slowly.
- Moderate measurement noise → daily prices contain microstructure noise.
- Ensures smooth yet reactive β_t updates.

Spread-Mean Filter (Kalman #2)

$$q = 10^{-4}, \qquad r = 10^{-2}$$

Justification:

- The mean-reversion level of the spread should drift gradually → small q.
- The spread itself is noisy → higher r.
- This keeps μ_t stable while still tracking structural changes.

Practical Estimation Approach

Before activating the hedge ratio Kalman filter, we perform a single OLS regression over the first window_size observation:

$$A_t = \beta B_t + \alpha.$$

This OLS estimation provides:

- Initial hedge ratio β_0,
- Initial intercept α_0,
- A stable starting point for the filter.

These values are injected into the initial Kalman state:

$$x_0 = [\beta_0, \alpha_0]^\top.$$

For the second filter (signal mean), no pre-estimation is required.

3.3 Reestimation Schedule and Validation Approach

The Kalman filters operate **recursively** and are re-estimated **every day**, following the SDA loop:

1. Predict
2. Observe
3. Update
4. Decide
5. Act
6. Learn

Full reinitialization across segments

For integrity of out-of-sample testing:

- The filter is **fully reinitialized** at the start of TRAIN, TEST, and VALIDATION.
- No information leaks from one segment to the next.
- This ensures clean statistical separation.

Validation Approach

Three data segments were used:

Segment	Purpose
Train	Fit hyperparameters, test filter stability
Test	Evaluate real performance
Validation	Perform final unbiased check

Performance metrics include:

- Sharpe
- Sortino
- Max drawdown
- Calmar ratio
- Stability (R^2)
- Full trade statistics

This ensures that the filter performs consistently across unseen data.

3.4 Convergence Analysis and Filter Stability

Hedge-Ratio Kalman Filter

The Kalman-smoothed hedge ratio rapidly stabilizes after the warm-up period. Early updates show greater dispersion due to the large initial covariance, but after roughly 50–100 steps the filter converges to a much smoother trajectory.
This reflects exactly what we observe in the validation plot:

- The hedge ratio curve is **very stable**,
- It stays close to a long-run equilibrium level,
- And only exhibits small gradual deviations when market conditions change.

This behavior is desirable: the hedge ratio becomes robust, smooth, and avoids overreacting to noisy price movements.

Mean-Reversion Signal Kalman Filter

Unlike the hedge-ratio filter, this filter **does not require pre-training**.
It begins tracking the moving mean immediately, gradually reducing the influence of noise as more observations accumulate.

From the validation chart:

- μ_t does **not** converge to a constant (as expected),
- Instead, it **follows slow structural drifts** in the spread,
- While filtering out high-frequency volatility.

This confirms the model behaves as intended: it extracts the low-frequency component of the spread needed to compute a stable and robust z-score.

Trading Strategy Logic

In this project, we implemented a dynamic mean-reversion pairs trading strategy based on cointegrated assets, enhanced using two Kalman filters. The core idea behind this approach is that if two assets share a stable long-term equilibrium relationship, deviations from this equilibrium can be exploited for trading opportunities. The filters give the strategy a dynamic component to update the parameters constantly, which in turn should make it more robust.

The first Kalman filter was used to estimate the time-varying hedge ratio between the paired assets. This hedge ratio is often static and calculated with an initial linear regression. However, by applying a Kalman filter, we were able to obtain a dynamically updated hedge ratio at each point in the sample. This allows the spread defined as the price of one asset minus the hedge-adjusted price of the other to more accurately reflect the true equilibrium relationship under current market conditions.

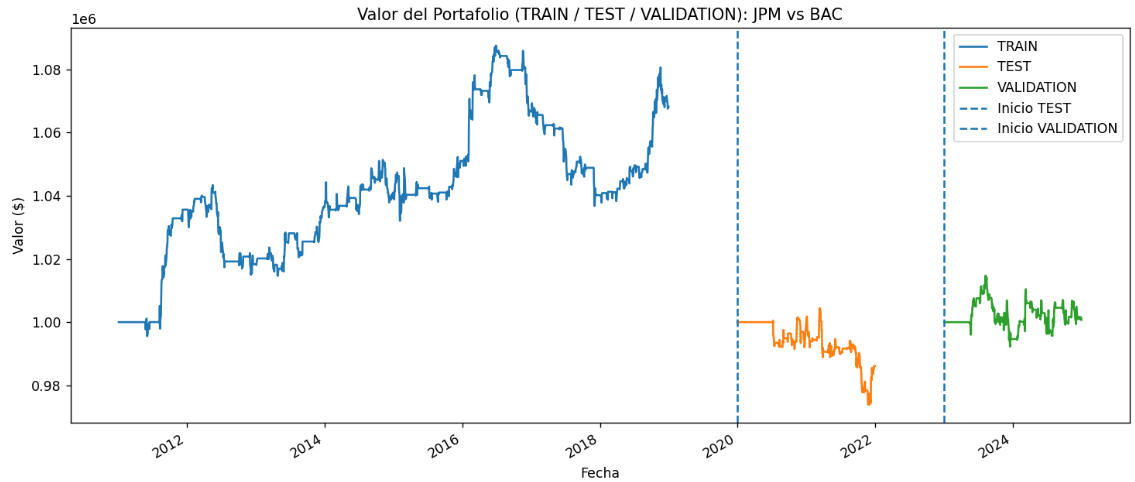
The second Kalman filter was then applied to the spread itself to generate the trading signals. This filter provides a smoothed and adaptive estimate of the mean and variance of the spread, enabling us to compute a reliable Z-score without relying on fixed rolling windows. The Z-score indicates how far the spread is from its estimated equilibrium in standardized units. When the Z-score becomes sufficiently large in magnitude, it signals that the spread has deviated from its expected mean and may soon revert, creating a potential trading opportunity.

To operationalize these signals, we used a theta value of 1, meaning that a trade would be opened whenever the Z-score exceeded ±1. Specifically, when the Z-score rose above +1, the spread was considered too high: we would short the spread by selling the overpriced asset and buying the underpriced one. Conversely, when the Z-score fell below –1, the spread was deemed too low: we went long the spread by buying the undervalued asset and shorting the overvalued one. Once a position was open, it was closed when the Z-score reverted toward equilibrium specifically, when it fell below a threshold very close to zero (0.15) indicating that the mean-reversion process had completed and profits could be locked in. It is important to note that a rolling window of 252 days was used to create the information needed in order to give information to the model.

Regarding the backtesting of the strategy, we used a specific approach that utilized a big amount of the portfolio value, following the assumptions that this approach is neutral to the market and would be hedged to not produce losses. In this case, 40% of the total amount of cash available would be traded at each "opening" sensed by the model. This would of course be balanced based on the hedge ratio produced by the first Kalman filter. Then, in turn, each long operation would be measured as a traditional buy operation, with commissions for opening and closing them. Short positions would be modelled as a short-sell, where we would acquire the asset whenever the position would close, opening and closing would imply both, commission costs each. Additionally, for each day that each short position would be open, a borrow-rate would be removed from the cash's available amount, paying for "owning" the asset without doing so.

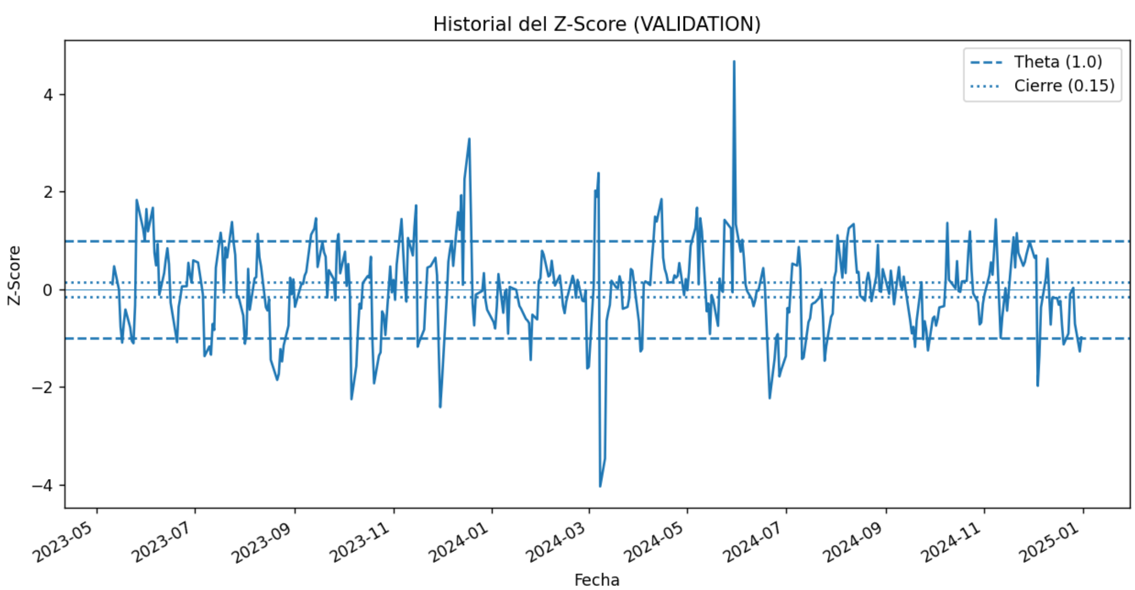
Results and Performance Analysis

Equity Curves



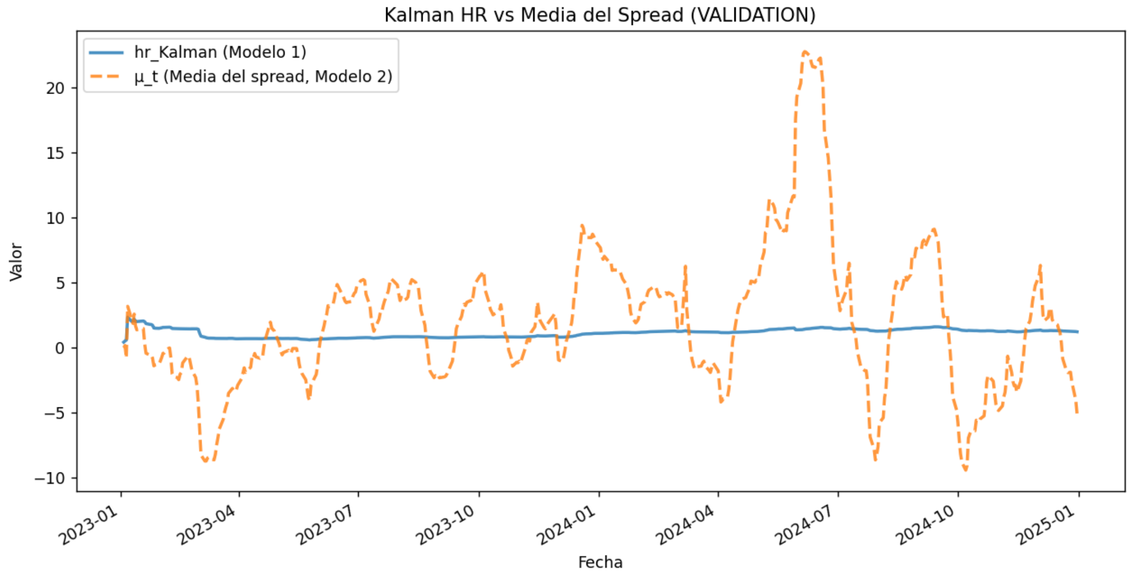
We can see that there is a steady growth in the portfolio's value throughout the first period, training, however, we lose consistency in the following. For the testing period, we se that there are many losses produced, and some little correction. For the validation part, we se a really steady equity curve, this may suggest that the model does not carry along correctly the signalling for data outside the sample.

Z-score historic (Validation)



We can see that the Z-score used to produce the signals seem stationary, as it should. Nevertheless, the equity for this time period was not optimally utilized by the model. This period produced none if any returns.

Kalman Filter Estimations



Then, we can analyse the predictions given by both Kalman filters. We se that the hedge ratio kept steady along the validation period, but the mean for the spread did change a lot. This may mean that the time series destabilized as time went on.

Strategy Perfomance

METRIC	TRAIN	TEST	VALIDATION
Annualized Return	0.0072	-0.0083	-0.0019
Annualized Volatility	0.0162	0.0152	0.0184
Sharpe Ratio	0.4447	-0.5441	-0.1020
Sortino Ratio	0.4702	-0.5108	-0.1243
Max Drawdown	-0.0376	-0.0277	-0.0198
Calmar Ratio	0.1918	-0.2988	-0.0950

Overall, the strategy shows acceptable performance during training but loses robustness and consistency once evaluated on unseen data. While the training metrics indicate stable returns, controlled volatility, and a positive risk-adjusted profile, the performance declines significantly in both the test and validation periods. Annualized returns shift from slightly positive to consistently negative, and Sharpe/Sortino ratios turn negative, signalling that the strategy fails to maintain an edge outside the calibration window.

The strategy demonstrates in-sample validity but out-of-sample weakness, indicating the need for stronger robustness checks, better regularization, or a more adaptive signal generation method.

Trade's Performance

STATISTIC	TRAIN	TEST	VALIDATION
Number of Trades	91	87	37
Win Rate	0.6484	0.5789	0.5135
Avg Win	$2878.7318	$1659.5260	$1918.0070
Avg Loss	-$3457.2071	-$3312.5893	-$2246.2081
Avg Return	0.0032	-0.0022	-0.0005
Total Gross Profit	$169,845	$36,509	$36,442
Total Gross Loss	-$110,630	-$53,001	-$40,431
Total Net PnL	$59,214	-$16,491	-$3,989
Total Commissions	-$46, 409	-$-18,771	-$18,570

The trade statistics reflect a similar pattern: profitable behaviour in training, but deterioration in real-world (test/validation) conditions. In training, the strategy shows a high win rate, and substantial gross profit. However, average losses exceed average wins, suggesting that profitability relies on frequency and not magnitude. Even in the favourable training environment, commissions consume a significant portion of gains, revealing high sensitivity to transaction costs.

Once the strategy is applied out-of-sample, trading performance declines sharply. Win rates drop, and net PnL becomes negative. Losses per trade become larger relative to wins, and commissions continue to erode performance materially. Holding periods shorten in test/validation, suggesting the strategy becomes more reactive but not more effective. These patterns highlight fragility in trade execution and insufficient resilience against market noise or structural changes.

Again, the performance reveals that the strategy becomes inconsistent out of the sample in which we trained and adapted the model. This reveals the need for a more robust signalling method, and a high sensitivity to commission costs.

Conclusions

This project highlights both the potential and the challenges of implementing a sophisticated pairs trading framework grounded in cointegration and enhanced by a Kalman Filter for dynamic parameter updating. The use of cointegration aims to ensure that selected asset pairs share a stable long-term equilibrium, forming the statistical foundation for mean-reversion signals. The Kalman Filter, in turn, provides a powerful mechanism to continuously update hedge ratios or equilibrium vectors as new data arrives, making the strategy more adaptive to evolving market conditions.

However, the overall performance results indicate that while the methodological approach is sound, the statistical tests and robustness checks require significant strengthening. True cointegration relationships are rare and sensitive to regime changes, making rigorous testing through Johansen procedures, ADF confirmation, stability analysis, and out-of-sample validation essential. In this implementation, the strategy performed acceptably in-sample but struggled out-of-sample, signalling that the pairs chosen may not possess sufficiently strong or stable cointegration properties, or that the strategy is overly sensitive to noise and transaction costs.

Despite the mixed performance, this project remains valuable as a practical exploration of an advanced quantitative framework. Replicating and testing a strategy that integrates cointegration theory, signal generation, and Kalman-based dynamic estimation offers meaningful insight into the complexities of real-world statistical arbitrage. Going forward, improving the rigor of the cointegration testing pipeline, enhancing robustness, and revisiting pair selection will be crucial steps toward achieving a reliable and deployable pairs trading model.