

QF621 Quantitative Trading Strategies

# **Pairs Trading: Application of Machine Learning and GARCH Model in the Foreign Exchange Market**

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# CONTENT

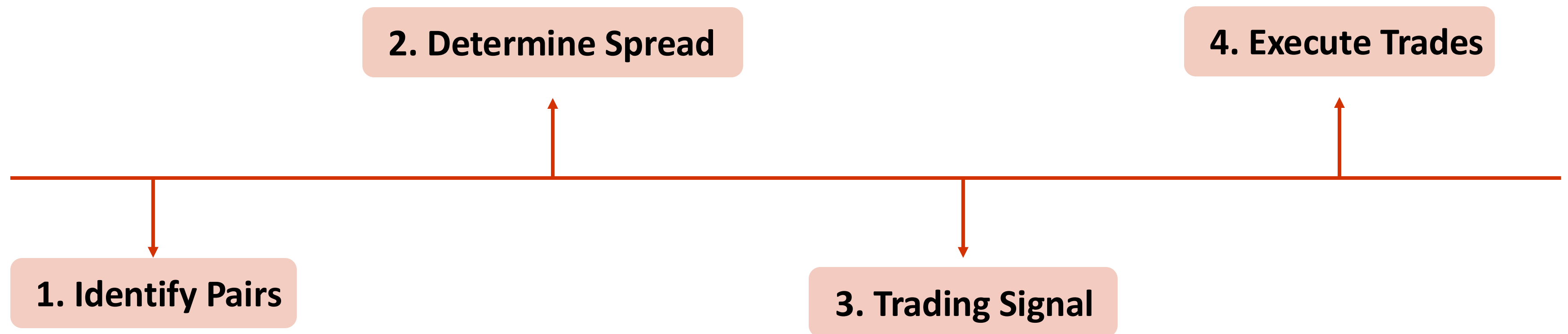
- 1 Introduction
- 2 Pairs Selection
- 3 Trading Signal
- 4 Back-testing Result
- 5 Discussion

# INTRODUCTION

## *Pairs Trading in Forex*

- Simultaneous long and short positions in two correlated currency pairs.
- Profits from the *relative price movements* rather than absolute price levels.
- *Exploits* mean reversion in correlated currency pairs.

## *Steps*



Project Overview

Data Source

➤ 35 historical Forex rates sourced from Yahoo Finance.

➤ Time frame: From 2014.01.01 to 2024.05.25

Pairs Selection	
Method	Introduction
Pure PCA Analysis	<div><div>• A <b>dimensionality reduction technique</b> that transforms a large set of variables into a smaller one that still contains <b>most</b> of the information.</div><div>• It identifies the <b>directions</b> (principal components) in which the data varies the most.</div></div>
PCA + OPTICS Clustering	<div><div>• Combine PCA with OPTICS to <b>leverage the strengths</b> of both techniques for finding trading pairs.</div><div>• OPTICS is a clustering algorithm that identifies clusters with <b>varying densities</b>, which helps in finding groups of assets that <b>behave similarly</b>.</div></div>

Project Overview

Pairs Selection

Method	Suitable for	Advantages
Pure PCA Analysis	<ul style="list-style-type: none"><li>Markets with <i>high volatility</i></li><li>Markets with significant <i>linear</i> relationships</li><li>Markets with <i>large data scales</i></li></ul>	<ul style="list-style-type: none"><li>Effectively captures the <i>primary directions</i> of variance</li></ul>
PCA + OPTICS Clustering	<ul style="list-style-type: none"><li><i>Diversified</i> markets</li><li><i>Complex</i> markets with significant <i>nonlinear</i> relationships</li><li>Markets with <i>strong local correlations</i></li></ul>	<ul style="list-style-type: none"><li>Identifies intricate market structures</li><li>Uncovers <i>potential</i> trading opportunities</li></ul>

Project Overview

Trading Signal

Method

Introduction

Traditional Methods

- Often involves *simple statistical techniques* to identify deviations from historical relationships between asset prices.

GARCH Model

- To model and *forecast time-varying volatility* in financial time series.

Project Overview

Trading Signal

Method	Suitable for	Advantages
Traditional Methods	<ul style="list-style-type: none"><li>Markets with <i>stable</i> volatility patterns</li><li>Markets with <i>fewer data points</i></li></ul>	<ul style="list-style-type: none"><li><i>Simple</i> and <i>easy</i> to implement</li><li><i>Quick</i> computation</li><li><i>Less</i> computational intensive</li></ul>
GARCH Model	<ul style="list-style-type: none"><li>Markets with <i>high and variable</i> volatility</li><li>Markets with <i>large</i> datasets and <i>high-frequency</i> data</li><li>Markets where <i>capturing volatility is crucial</i></li></ul>	<ul style="list-style-type: none"><li>Models time-varying volatility <i>explicitly</i></li><li><i>More accurate</i> spread estimation under conditions</li><li>Provides a <i>more realistic</i> measure of risk</li></ul>



# PAIRS SELECTION

PCA and OPTICS

State 0  
1. Price Series

1. Dimensionally Reduction

Calculate Correlation Matrix

Apply PCA

Apply PCA on Training Set



Relative return

$$\frac{\text{New Price} - \text{Old Price}}{\text{Old Price}} \times 100\%$$

Transform to Standard Normal

Calculate Correlation Matrix

State 1  
1. Price Series  
2. PCA representation

2. Unsupervised Learning

Apply OPTICS

Minimum samples value = 2  
Maximum epsilon value = Infinity  
*(Setting to infinity allows OPTICS to determine the optimal epsilon)*

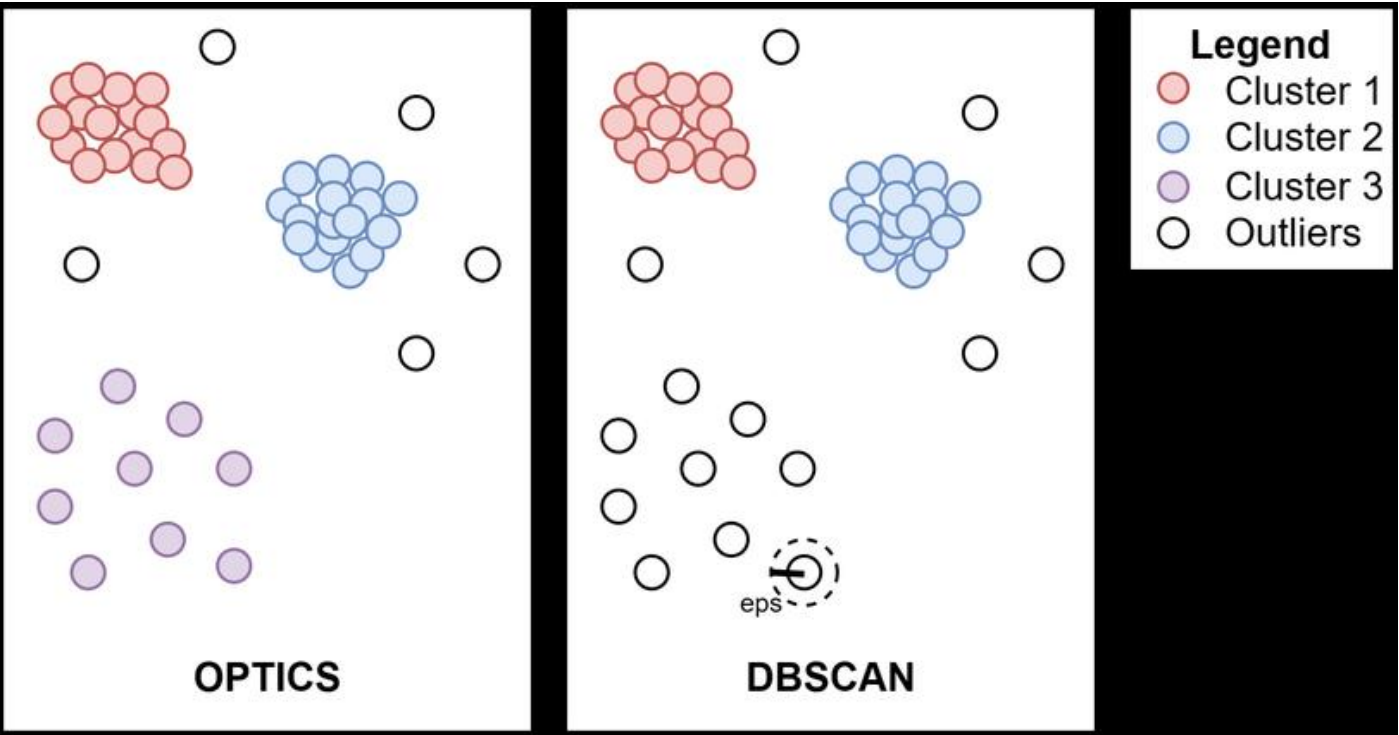
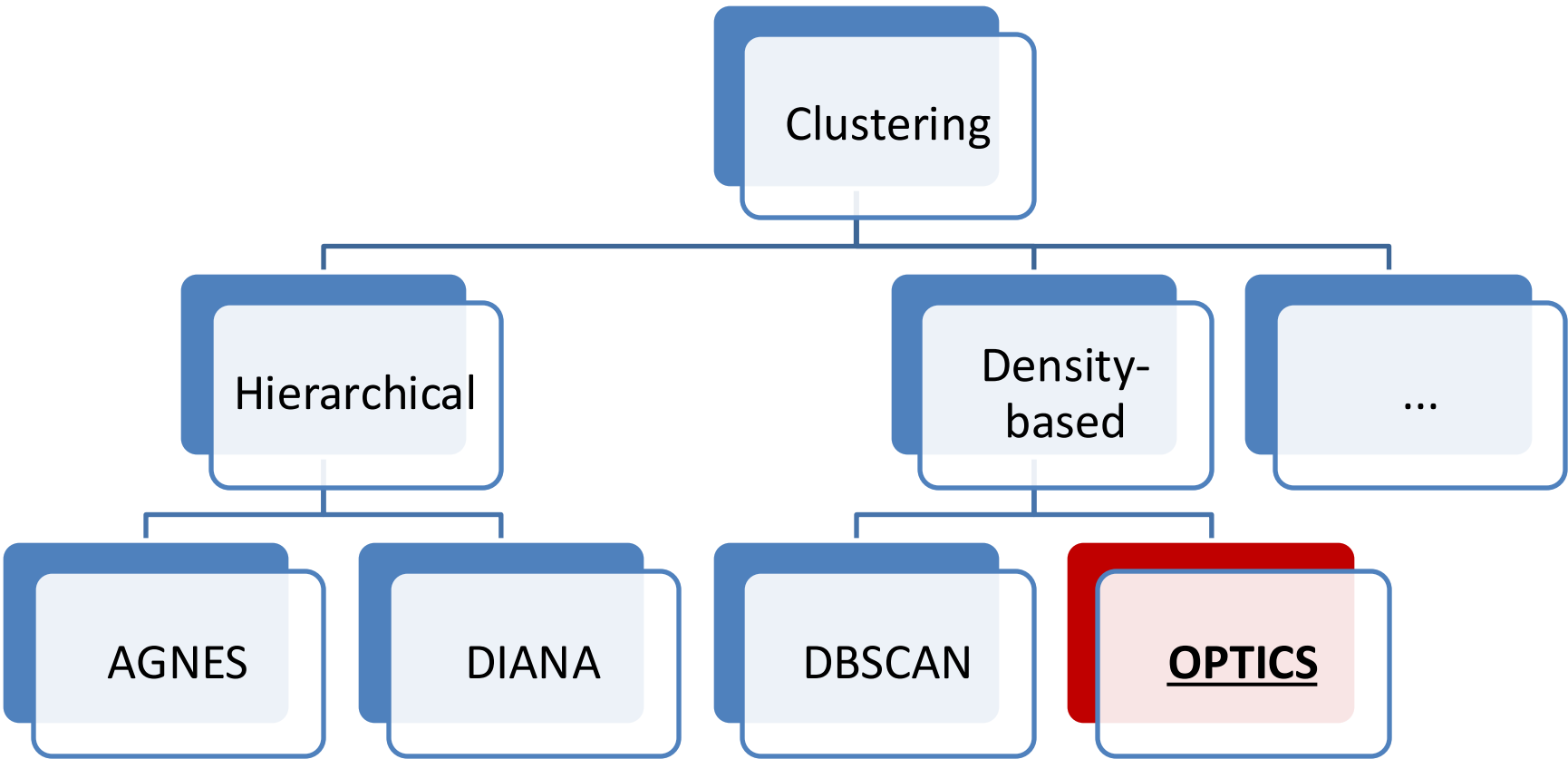
State 2  
1. Price Series  
2. PCA representation  
3. Clusters for search

3. Select Pairs

Apply rules

State 3  
1. Price Series  
2. PCA representation  
3. Clusters for search  
4. Selected Pairs

# What is OPTICS Clustering?



### *Check for Cointegration & Stationarity*

#### **Step 2** *Log-Transform the Prices*

- To stabilize variance and convert multiplicative relationships into additive relationships.

#### **Step 4** *Perform Engle-Granger Cointegration Test*

- Reject if p-value > 0.5.

#### **Step 1** *Identify the Most Influential Assets*

- Identify the assets with the highest and lowest absolute loading in the principal component.

#### **Step 3** *Perform OLS Regression*

- $\beta$ : hedge ratio

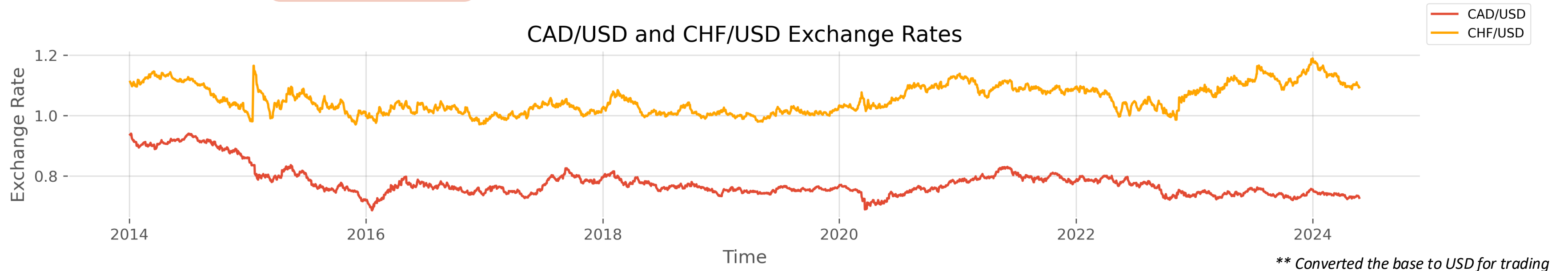
#### **Step 5** *Perform ADF Test for Stationarity*

- Performed on the residuals.
- Reject if p-value > 0.5.

## PCA Results

**CAD=X and CHF = X**

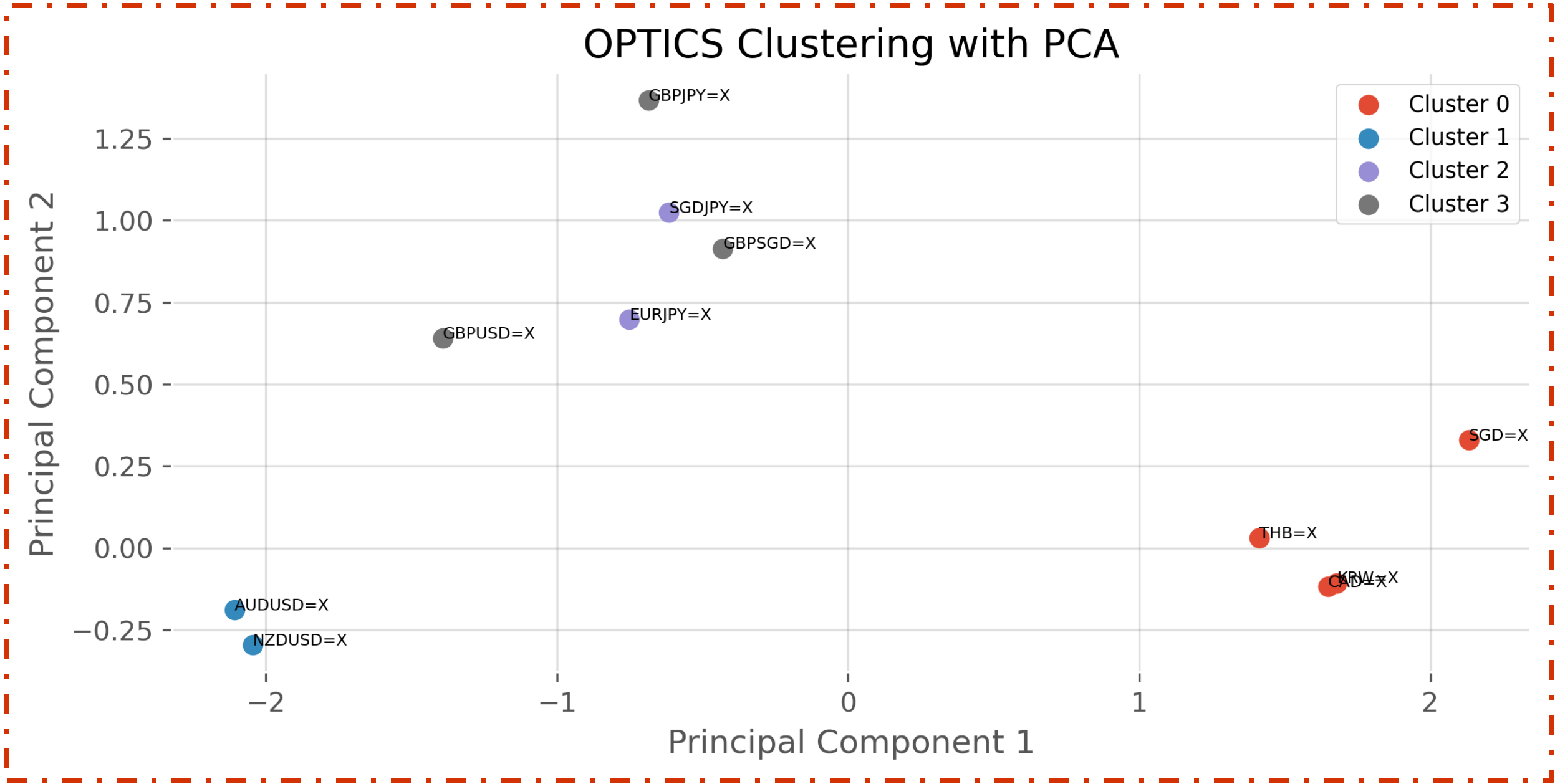
(US Dollar / Canadian Dollar and US Dollar / Swiss Franc)



## Economic Intuition

- **Different Economic Drivers:**
  1. **CAD = X** : Heavily influenced by the *commodity market*, particularly oil.
  2. **CHF = X**: Often considered a *safe-haven currency*.
- **Correlation and Diversification:**
  1. **Correlation**: Low correlation (*0.3160*) due to the different economic factors.
    - Opportunity for pairs trading, as the spread between them might offer mean-reverting characteristics.
  2. **Diversification**: The trader can potentially hedge against *sector-specific risks*.

PCA + OPTICS Results



List of Noisy Points:

SGDMYR=X, EURSGD=X, SGDHKD=X, SGDIDR=X, SGDCNY=X, SGDTHB=X, SGDINR=X, SGDKRW=X, AUDSGD=X, NZDSGD=X, JPY=X, HKD=X, MYR=X, INR=X, CNY=X, PHP=X, IDR=X, CHF=X, MXN=X, VND=X, EURGBP=X, EURSEK=X, EURCHF=X, EURHUF=X

Cluster	Currency
0	SGD = X
	THB = X
	KRW = X
	CAD = X
1	AUDUSD = X
	NZDUSD = X
2	SGDJPY = X
	EURJPY = X
3	GBPSGD = X
	GBPJPY = X
	GBPUSD = X

Total11 pairs

PCA + OPTICS Results

Cluster	Currency
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0	SGD = X
	THB = X
	KRW = X
	CAD = X

Based on *USD pairings*, with significant trade relations with the US and influences from US economic data.

1	AUDUSD = X
	NZDUSD = X

Due to *geographic proximity* and *similar economic structures*, heavily influenced by commodities and USD.

2	SGDJPY = X
	EURJPY = X

Based on the common involvement of the *Japanese Yen*, influenced by its safe-haven status and interest rate differentials.

3	GBPSGD = X
	GBPJPY = X
	GBPUSD = X

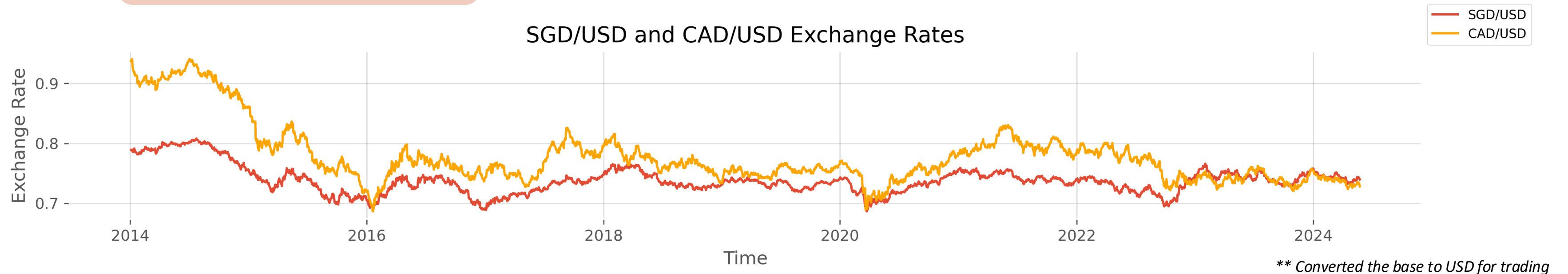
Due to the common involvement of the *British Pound*, reflecting its global economic influence and diverse economic links.

Economic Explanation for the Clusters

## PCA + OPTICS Results

SGD=X and CAD = X

(US Dollar / Singapore Dollar and US Dollar / Canadian Dollar)



### Economic Intuition

#### ➤ Economic Divergence:

1. **SGD:** A highly developed and open economy, heavily reliant on *trade* and *services*.
2. **CAD:** Heavily influenced by the *commodity market*, particularly oil.

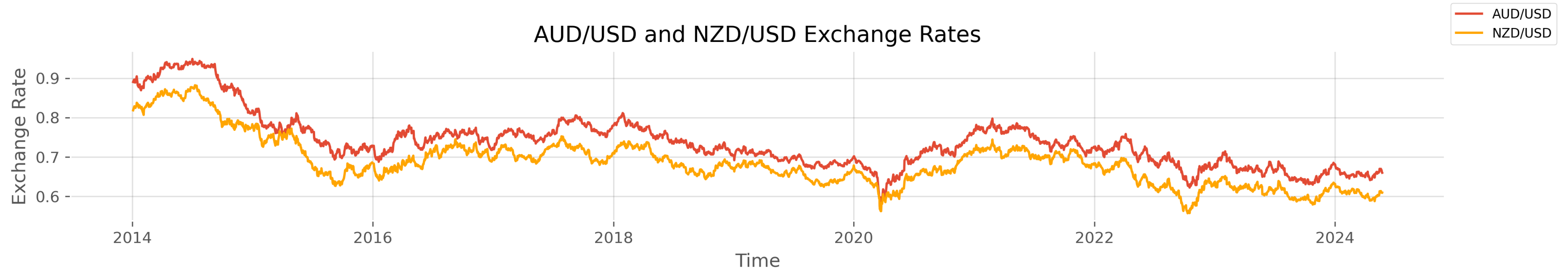
#### ➤ Interest Rate Differentials:

1. **SGD:** MAS uses the *exchange rate* as the main tool of monetary policy rather than interest rates.
  - Interest rates in Singapore are influenced by *global interest rates* and the *domestic economy's performance*.
2. **CAD:** Bank of Canada's *interest rate decisions* directly impact the CAD.
  - Higher interest rates in Canada attract foreign investment, strengthening the CAD, while lower rates can weaken it.



**PCA + OPTICS Results****AUDUSD=X and NZDUSD = X**

(Australian Dollar / US Dollar and New Zealand Dollar / US Dollar)

**Economic Intuition**➤ **Economic Structures:**

1. **Australia:** A *diverse economy* with key sectors including mining, agriculture, services, and manufacturing.
2. **New Zealand:** A *smaller, open economy* heavily reliant on agriculture and dairy products.

➤ **Geopolitical Factors:**

- Both countries have relatively *stable* political environments, but they can be affected by global geopolitical events that impact trade, commodity prices, and investor sentiment.

TRADING SIGNAL

Traditional Method

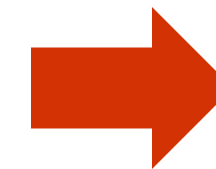
1 Generate Spread Series

From OLS Regression

Intercept	Coefficient
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$$MSPREAD = Y_t - (a + bX_t)$$

Log price series of 2 assets



Decentralization

2 Calculation of Mean and Standard Deviation

$$\mu = \frac{1}{N} \sum_{t=1}^N MSPREAD_t$$
$$\sigma = \sqrt{\frac{1}{N} \sum_{t=1}^N (MSPREAD_t - \mu)^2}$$

3 Construction of Trading Signals

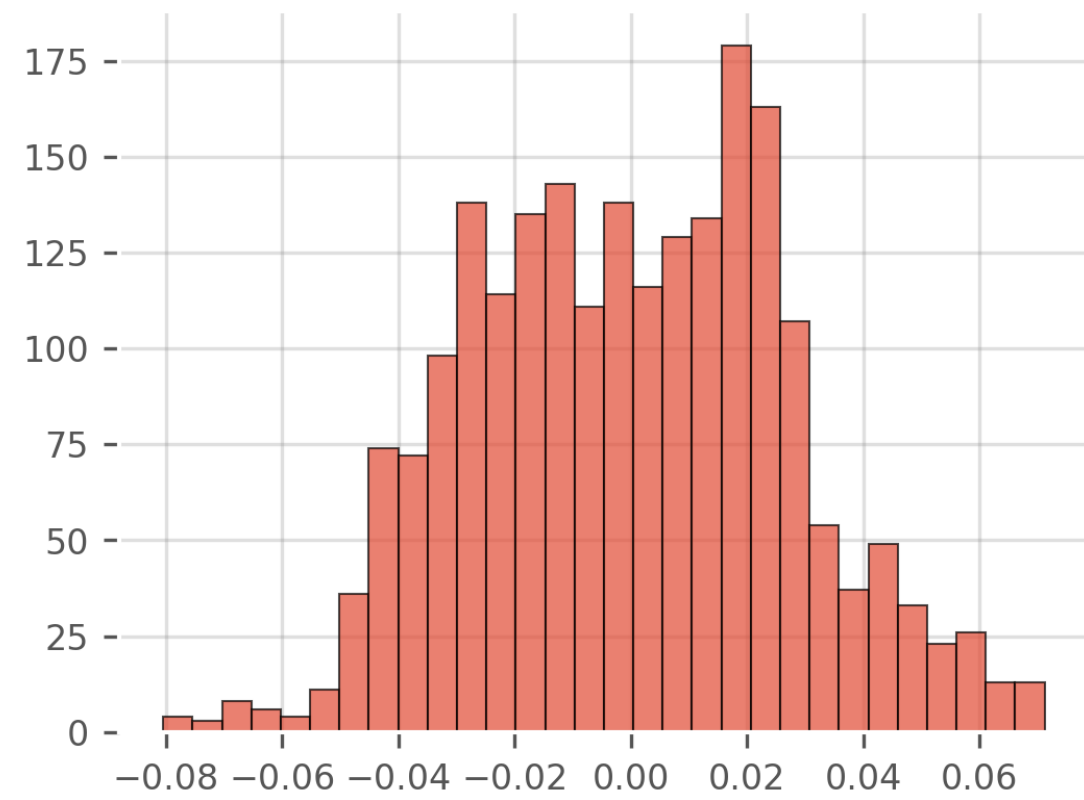
$$\text{Buy Signal} = MSPREAD_t < \mu - k\sigma$$
$$\text{Sell Signal} = MSPREAD_t > \mu + k\sigma$$

In our project, we set  $k = 1$ .

Traditional Method

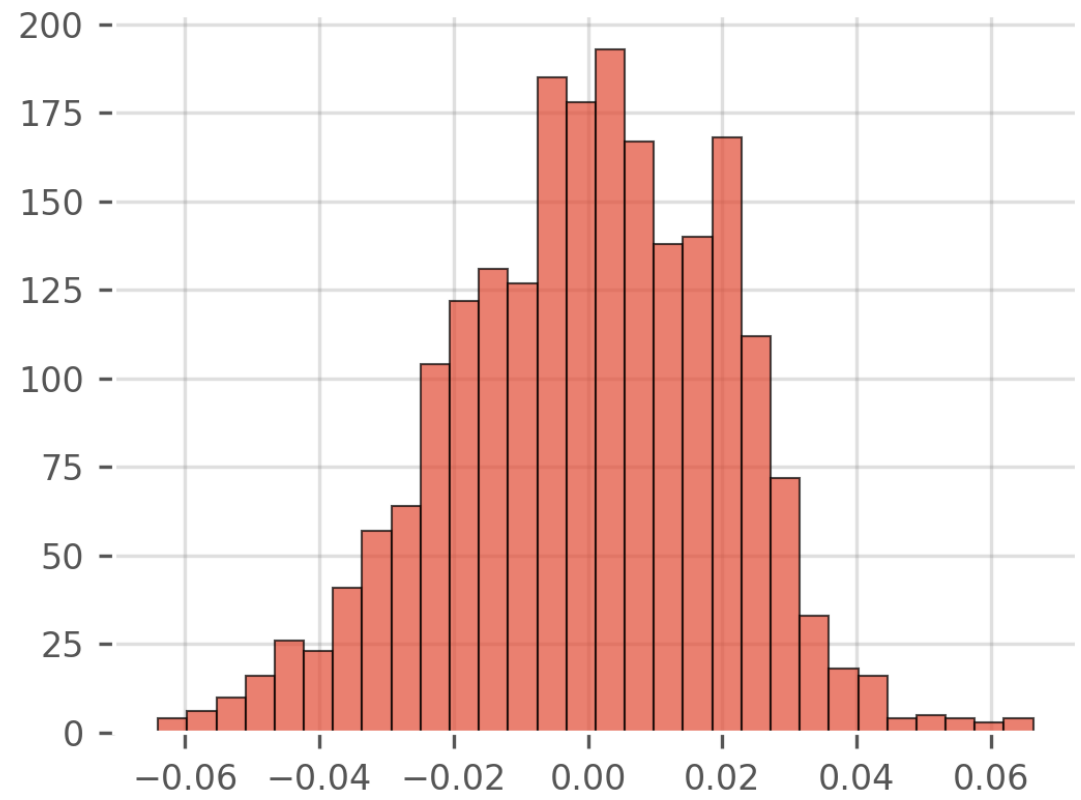
Descriptive Statistics of Decentralized Spread Series

SGD = X and CAD = X



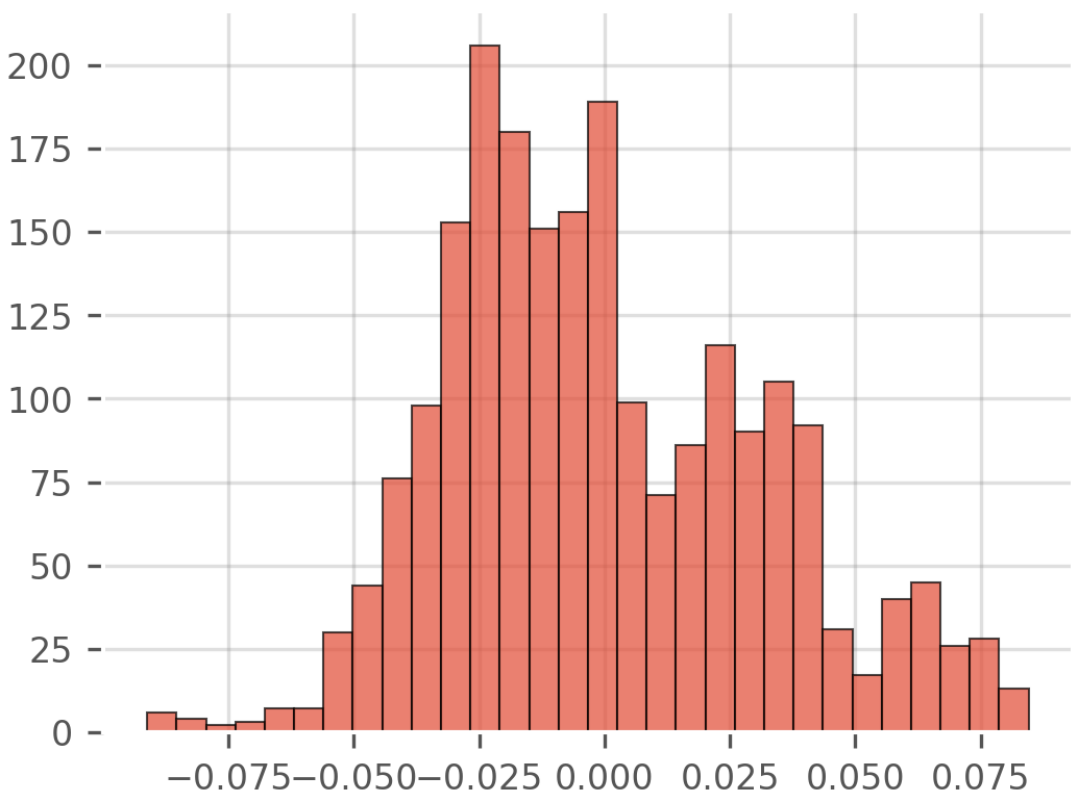
Mean = 0  
Std. Dev. = 0.0272  
Skewness = 0.0584  
Kurtosis = 2.5515  
Jarque-Bera Stats. : 19.4320  
P-value (JB Test): 0

AUDUSD = X and NZDUSD = X



Mean = 0  
Std. Dev. = 0.0205  
Skewness = -0.1962  
Kurtosis = 2.9459  
Jarque-Bera Stats. : 14.1902  
P-value (JB Test): 0.0008

CAD = X and CHF = X



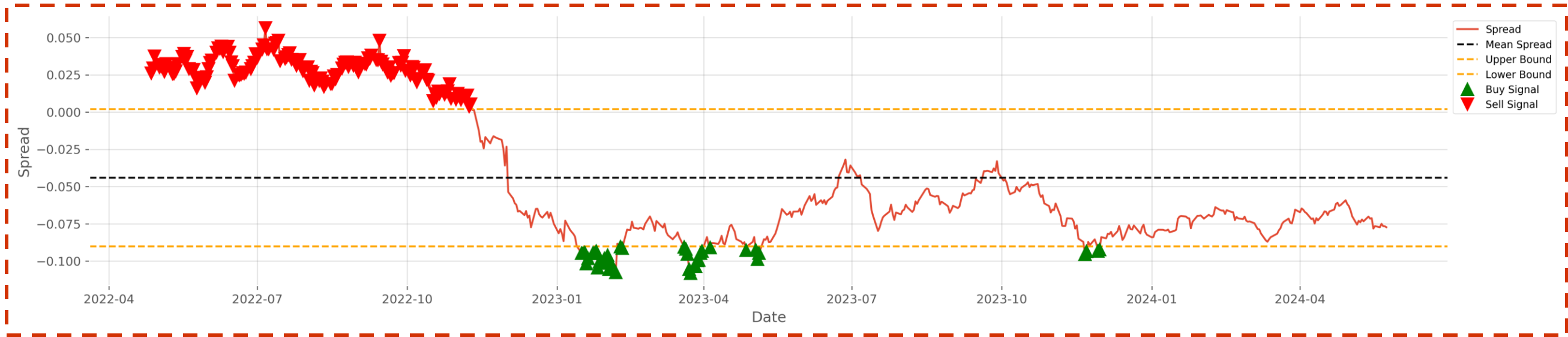
Mean = 0  
Std. Dev. = 0.0318  
Skewness = 0.4245  
Kurtosis = 2.7480  
Jarque-Bera Stats. : 70.9398  
P-value (JB Test): 0.0000

Traditional Method

Construction of Trading Signals

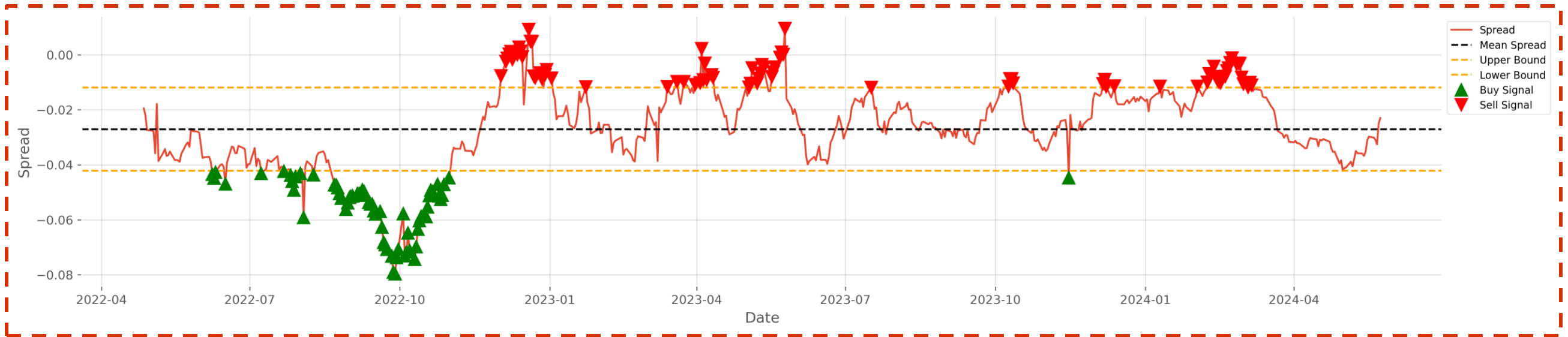
SGD = X and CAD = X

Holding: 365  
Sell: 141  
Buy: 37



AUDUSD = X and NZDUSD = X

Holding: 400  
Sell: 78  
Buy: 65



CAD = X and CHF = X

Holding: 316  
Sell: 140  
Buy: 87



## GARCH Model Method

### 1 Fitting an AR(2) Model

$$MSPREAD_t = c + \sum_{i=1}^p \phi_i MSPREAD_{t-1} + \epsilon_t$$

Constant  $\swarrow$   $\searrow$  Lag coefficients

### 2 Fitting a GARCH Model to AR(2) residuals

$$\epsilon_t = \alpha_0 + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2$$

$\epsilon_t$  from AR(2) model  $\rightarrow$  **Forecast  $\sigma^2$**

### 3 Adjust the spread

$$Adj.SPREAD_t = MSPREAD_t - c - \sum_{i=1}^p \phi_i MSPREAD_{t-1}$$

### 4 Construction of Trading Signals

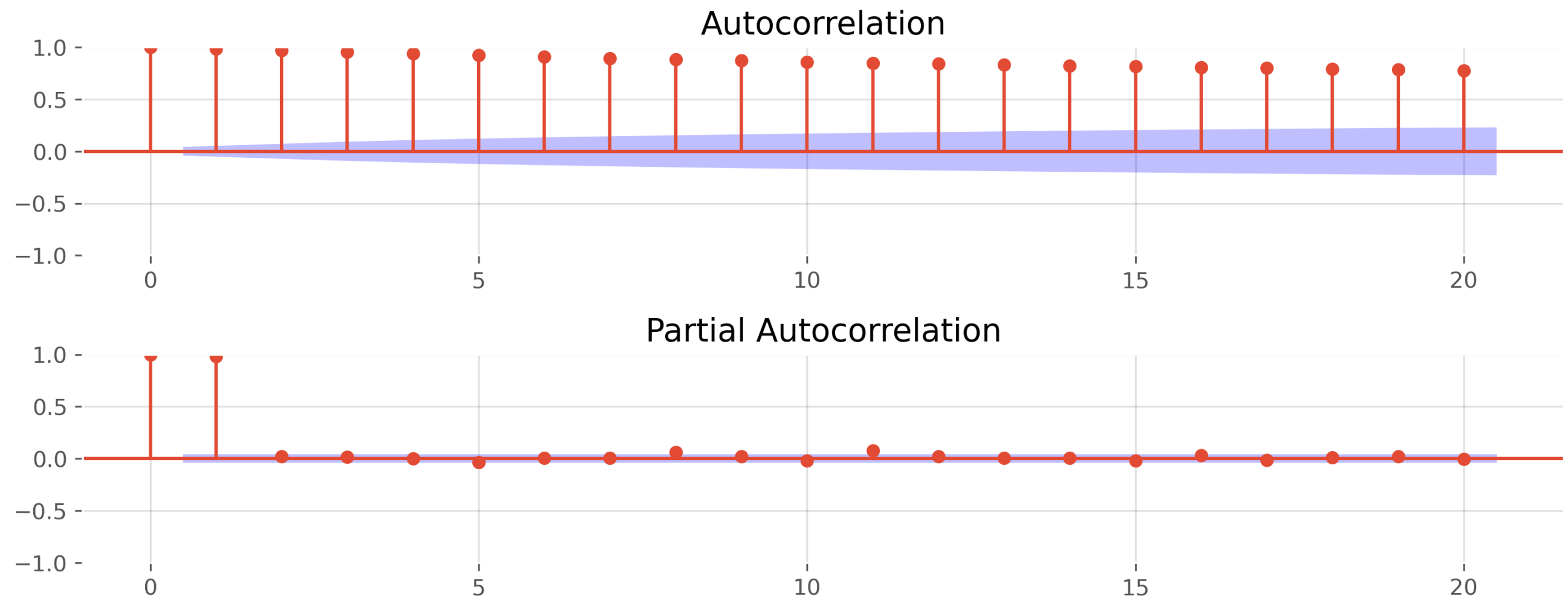
$$Buy\ Signal = Adj.SPREAD_t < -k\sigma$$

$$Sell\ Signal = Adj.SPREAD_t > k\sigma$$

*In our project, we set  $k = 1$ .*

**GARCH Model Method**

***Autocorrelation Test (All the pairs have the same results.)***



***PACF***

Significant spikes at lag 1 and 2 and then fluctuates around zero.

***ACF***

A slow decay.

***AR(2)***

**GARCH Model Method**

**ARCH-Lagrange Multiplier Test**

- To indicate evidence of heteroskedasticity in the residuals of the GARCH(1,1) model.
  - P-value > 0.05 : Homoskedasticity
  - P-value < 0.05 : Heteroskedasticity

***SGD=X and CAD=X***

Lagrange Multiplier Test Statistic: 24.1818  
p-value: 0.0071

***AUDUSD = X and NZDUSD = X***

Lagrange Multiplier Test Statistic: 30.9759  
p-value: 0.0006

***CAD = X and CHF = X***

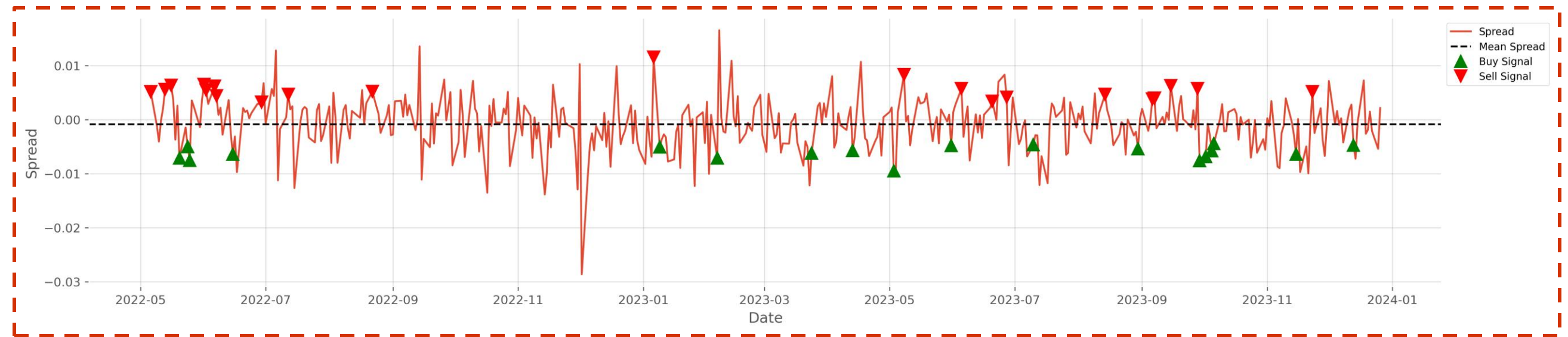
Lagrange Multiplier Test Statistic: 42.6111  
p-value: 0.0

 ***Heteroskedasticity***



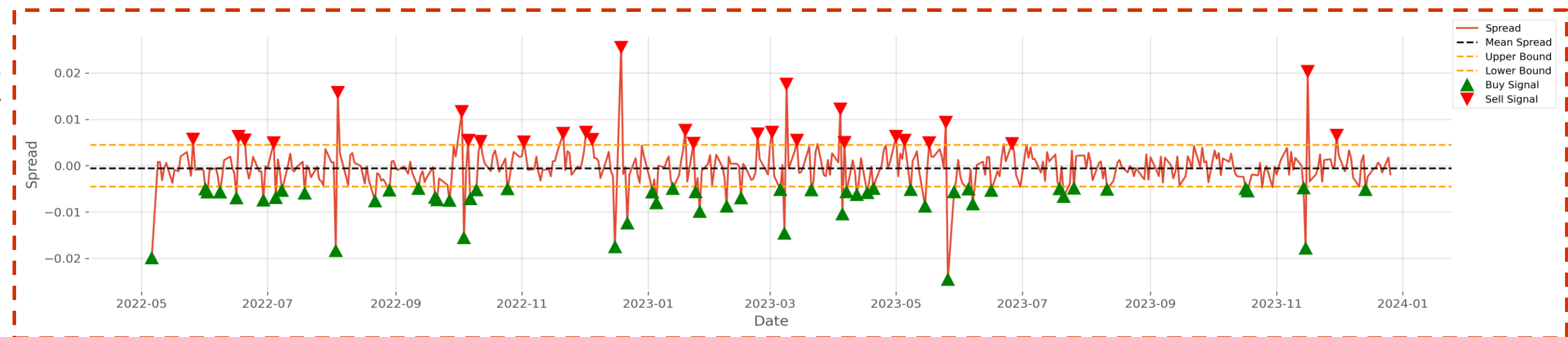
SGD = X and CAD = X

Holding: 315  
Sell: 38  
Buy: 75



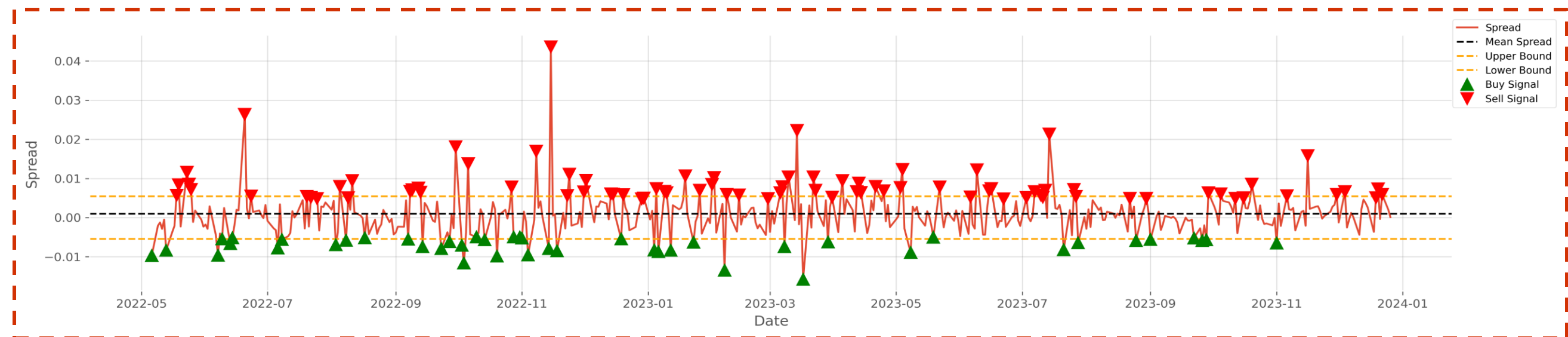
AUDUSD = X and NZDUSD = X

Holding: 347  
Sell: 28  
Buy: 53



CAD = X and CHF = X

Holding: 299  
Sell: 84  
Buy: 45



# BACK-TESTING RESULT

Leverage

When it is **Buy Signal** -> Buy  $\beta$  spread and vice versa.

Where  $\beta$  is the OLS estimation coefficient

Back Testing Metrics

Cumulative Return

Sharpe Ratio

Sortino Ratio

Max Drawdown (%)

Cumulative of daily return

$$\sqrt{252} \times \frac{\text{Average Value of Daily Return}}{\text{Standard Deviation of Daily Return}}$$

$$\sqrt{252} \times \frac{\text{Average value of daily return}}{\frac{\sum \text{Daily Return}^2}{\sqrt{\text{Number of Days}}}}$$

$$\max \left( \frac{\text{Maximum Drawdown (\$)}}{\text{Cumulative Maximum portfolio value}} \times 100\% \right)$$

Methods	Pairs	Cumulative Return (%)	Sharpe Ratio	Sortino Ratio
Traditional	SGD = X and CAD = X	7.55	0.54	0.87
	AUDUSD = X and NZDUSD = X	6.87	0.5	0.71
	CAD = X and CHF = X	7.64	0.43	0.78
GARCH Model	SGD = X and CAD = X	3.56	0.15	0.25
	AUDUSD = X and NZDUSD = X	37.97	0.61	0.96
	CAD = X and CHF = X	13.29	0.57	0.97

## Key Observations

### 1 Superior Performance of GARCH Model

- This suggests that the GARCH model is more effective in capturing and utilizing volatility information for generating trading signals.

### 2 Enhanced Risk Management

- Lower drawdown reflects the GARCH model's ability to adapt to changing market conditions and mitigate significant losses during adverse periods.

### 3 Consistency Across Pairs

- The performance improvement with the GARCH model was consistent across all tested currency pairs.
- This consistency enhances the credibility of the GARCH model as a robust tool for pairs trading strategies across different forex markets.

### 4 Weak Performance of PCA Pair

- Weak performance for the CAD=X and CHF=X pair in both methods, with smallest Sharpe and Sortino ratios.
- The poor performance of the PCA pair can be attributed to its inability to effectively capture complex, non-linear relationships and varying densities within the data.

# DISCUSSION

### *Weakness of the Technique*

#### **1 High Computational Requirements**

- The GARCH model is computationally intensive, requiring significant processing power and advanced technical expertise.

#### **2 Data Dependency**

- The strategy relies heavily on historical data to model volatility and generate trading signals.
- This dependency can be a limitation as past performance does not always predict future results, especially in rapidly changing markets.

#### **3 Market Assumptions**

- Pairs trading strategies, including those using the GARCH model, often assume that the price relationship between pairs will revert to the mean.
- If this assumption does not hold true, especially during prolonged trends or structural market changes, the strategy may incur losses.

### *Areas for Further Research*

1

#### **Incorporation of Macro-Economic Indicators**

- Understanding the broader economic context may help in anticipating market movements more accurately.

2

#### **Sentiment Analysis**

- Incorporating sentiment analysis from news articles, social media platforms, and financial forums could provide additional insights into market sentiment.
- This can help in capturing market moods and trends that are not reflected in historical price data alone.

3

#### **Regime Switching Models**

- Combining the GARCH model with regime-switching models could help in identifying different market regimes (e.g., bull, bear, high volatility, low volatility).
- Adapting trading strategies based on the identified regime can improve performance and risk management.

4

#### **High-Frequency Data**

- Exploring the application of the GARCH model to high-frequency data can provide opportunities for intraday trading.



The background features abstract orange shapes. On the left, a large, flowing, organic shape curves upwards. On the right, a smaller, more defined shape with a wavy bottom edge is positioned near the top, with two small solid orange circles below it.

THANK  
YOU