Adaptive Spread Strategy:

A Causal Framework for Equity Pair Trading

Rule-Based Statistical Arbitrage on Borsa İstanbul

Backtested 2020–2024

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Independent quantitative research note. Python (pandas, matplotlib) for simulation and analysis; LaTeX for documentation.

Abstract

This report develops and evaluates a rule-based *adaptive spread* trading framework for Turkish equities. The objective is to deliver repeatable mean-reversion alpha under realistic financing and execution constraints without predictive modeling or information leakage. The approach combines causal rolling estimation, volatility-adaptive windowing for both β (hedge ratio) and Z-score construction, and a strictly chronological walk-forward selection of pairs for the test horizon. A Prime Broker–style simulator implements capital allocation via Z-magnitude scaling with utilization, margin, fees, slippage, borrow, and rebate mechanics. Using Borsa İstanbul daily data (2016–2024) and TCMB policy rates (2020–2024), the base configuration compounds 1.0 million to 6.3 million over 2020–2024 (multiple 6.33×, CAGR 44.7 %, Sharpe 2.5, max drawdown 24.6 %). Alpha-only results (net of costs) reach 3.1 million, while carry adds 3.2 million. A like-for-like risk-free benchmark ends at 2.7 million, implying an excess multiple of 2.3×. Results are robust across exit and sizing scenarios, confirming that disciplined causal construction and adaptive exposure are sufficient to sustain performance without ex-post optimization.

Keywords: statistical arbitrage, mean reversion, causal modeling, pair trading, Turkey

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1 Introduction

Pair trading, a canonical form of statistical arbitrage, exploits the tendency of related securities to revert toward a long-term equilibrium relationship. Practical implementations, however, often fail to generalize beyond backtests due to (i) fixed lookbacks that lag regime shifts, (ii) unrealistic financing/cost assumptions, and (iii) implicit information leakage. The framework here addresses these with causal rolling estimation, volatility-adaptive windowing, and strictly walk-forward validation. Each stage—from data acquisition to portfolio simulation—is modular, reproducible, and deployable.

Across 2020–2024, the base strategy compounds capital from 1 million to 6.3 million (6.33×; CAGR 44.7 %), Sharpe 2.5, max drawdown 24.6 %. Against a risk-free compounding benchmark of 2.7 million, the strategy delivers an 2.3× excess multiple.

2 Data Collection and Preparation

Daily Borsa İstanbul equities (2016–2024; TRY) are obtained from Yahoo Finance (`yfinance`) and standardized to OHLCV Parquet files. The universe excludes index symbols (XU030, XU100) and contains 55 equities after cleaning. TCMB policy rates (2020–2024) are integrated for financing and idle cash modeling. Directory structure:

```
data/
 raw/           # Yahoo parquet files
 daily/         # Cleaned OHLCV data
 trade_data/    # all_trades.parquet
 wf_pairs/      # wf_pairs_YYYY.csv
 rate_data/     # TCMB rate history
```

3 Strategy Architecture

A causal, adaptive pipeline estimates equilibrium relationships and reversion dynamics.

Adaptive Spread Computation

Implemented in `adaptive_spread_strategy.py`:

1. Merge daily close prices, keeping overlapping dates only.

2. Log-transform to linearize proportional changes: $\mathrm{logP}_t = \ln(P_t)$.

3. Estimate rolling β (90 days): $\mathrm{logP}_1 = \alpha + \beta \mathrm{logP}_2 + \varepsilon$.

4. Construct spread: $S_t = \log P_{1,t} - \beta_t \log P_{2,t}$.
5. Compute causal volatility of ΔS (60 days, EMA-smoothed).
6. Map volatility $\rightarrow$ lookbacks ($\beta_{\text{win}} \in [30,90]$, $z_{\text{win}} \in [15,30]$).
7. Compute causal Z-score: $Z_t = \frac{S_t - \mu_t}{\sigma_t}$ with lagged μ_t, σ_t.

Signal Logic

Enter short when $Z_t > 1.5$ (two-bar confirm); enter long when $Z_t < -1.5$; exit when $|Z_t| < 0.5$ or after 60 days.

Principles

Causality (no lookahead), adaptivity (volatility-mapped windows), transparency (full logs), and consistency (base config shared across tests).

4 Walk-Forward Pair Selection

`walkforward_pair_selection.py` defines the annual universes (2020–2024) under strict causality.

For each year Y, filter trades with Entry Time in $[Y - 2\text{years}, Y)$. Compute count, mean, std, and Sharpe-like ratio:

$$\text{SharpeLike} = \frac{\text{Mean Return}}{\text{Std Return}}.$$

Exclude pairs with < 5 trades or bottom 20 %SharpeLike (nonpositive mean). Apply sector priors (same-sector boost or cross-sector whitelist). Rank remaining pairs by EMA-based Quality Score:

$$\text{QS} = \frac{\text{EMA(Return)}}{\text{EMA(Volatility)}}, \quad \alpha = 0.20,$$

and select Top 25 pairs per year. Files saved as `wf_pairs_Y.csv`. This ensures chronological fidelity and sector diversification.

5 Portfolio Simulation

`simulate_portfolio.py` evaluates performance with Prime Broker–style financing and execution.

Execution

For each year (2020–2024), rebuild trades for that year's pair list and execute entries within that year only, strictly chronologically. Daily capital updates include PnL, fees, and carry.

Sizing and Z-Magnitude Scaling

$$\text{Alloc}_i = f \times C_t \times \text{clamp}\left(\frac{|Z_{\text{entry}}|}{1.5}, 0.8, 1.4\right),$$

with $f = 0.06$, min alloc 50,000, utilization cap 0.98, max 24 positions. Stronger signals $\rightarrow$ larger allocations within bounds.

Costs and Financing

Commission 8 bps; slippage 4 bps; short margin 18 %; borrow 2 %annual; rebate spread 1 %; short cash credit 90 %. Idle cash earns TCMB deposit rate (daily compounded).

6 Portfolio Performance Analysis

Base Run (Z-scale [0.8–1.4])

End 6.33 M (6.33×); CAGR 44.7 %; Vol 15.2 %; Sharpe 2.51; Alpha Sharpe 1.11; Max DD 24.6 %. Alpha-only 3.11 M; Carry 3.22 M; Risk-free benchmark 2.74 M (excess multiple 2.3×).

Scenario Configurations

Scenario	Entry Z	Exit Z	Z-Scale Clamp [min–max]
base_run	±1.5	±0.5	[0.8–1.4]
exit_tight	±1.5	±0.25	[0.8–1.4]
zscale_fixed	±1.5	±0.5	[1.0–1.0]
zscale_wide	±1.5	±0.5	[0.5–2.0]

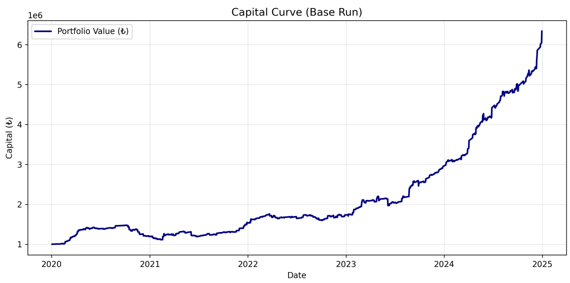
Performance Summary

Scenario	End Cap (million)	CAGR (%)	Vol (%)	Sharpe	Sharpe$_\alpha$	Max DD (%)	Comment
base_run	6.3	44.7	15.2	2.5	1.1	24.6	Balanced profile
exit_tight	5.7	41.8	16.1	2.3	1.0	19.1	Lower DD
zscale_fixed	6.2	43.9	13.0	2.9	1.2	20.9	Highest Sharpe
zscale_wide	6.5	45.5	16.2	2.4	1.1	26.4	Highest CAGR

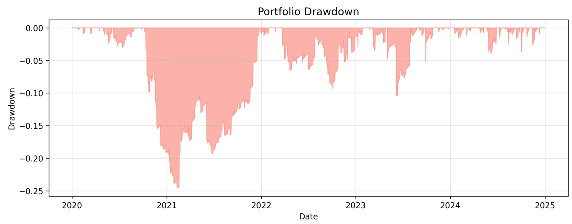
Interpretation. All scenarios outperform the risk-free benchmark. Bounded Z-magnitude scaling drives risk-adjusted efficiency (highest in `zscale_fixed`); wider clamps maximize CAGR but increase drawdown. The base configuration balances growth and risk for deployable robustness.

7 Results & Conclusion

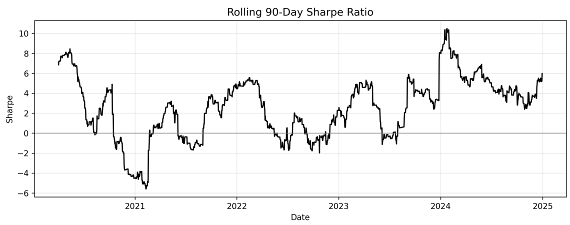
The framework achieves repeatable alpha under realistic constraints: 6.33× capital growth (2020–2024) at Sharpe 2.5 and max DD 24.6 %, roughly half from carry layered on top of alpha. Causal estimation, adaptive windows, and walk-forward selection ensure chronological integrity; PB-style modeling ensures execution realism. Performance is sustained without predictive models or leverage inflation.



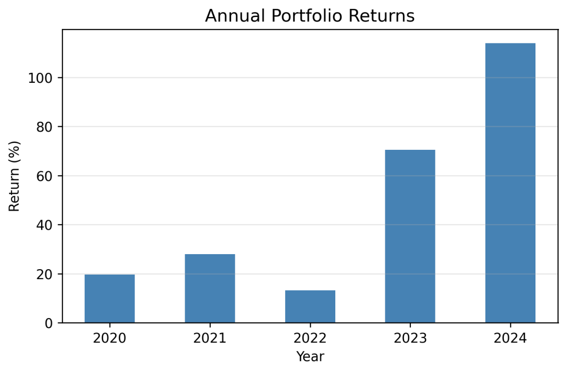
(a) Capital Curve (Base Run) — Portfolio value progression () from 2020–2024.



(b) Portfolio Drawdown — Maximum depth 24 %with consistent recoveries.



(c) Rolling 90-Day Sharpe — Temporal consistency of risk-adjusted returns.



(d) Annual Portfolio Returns (2020–2024) — Steady growth, peaking in 2023–2024.

Figure 1: Base-run performance visuals summarizing compounding, drawdowns, Sharpe stability, and inter-annual variability.

Appendix A – Parameter Summary

Parameter	Symbol	Value	Description
Commission	c_f	8 bps	Roundtrip fee
Slippage	s	4 bps	Execution impact per trade
Borrow Fee	b	2 %annual	Short borrow rate
Rebate Spread	r	1 %annual	Deposit – rebate differential
Short Margin Requirement	m	18 %	Collateral per short leg
Short Cash Credit	k	90 %	PB credit on short proceeds
Utilization Cap	$u_{\max}$	0.98	Max gross / capital ratio
Base Fraction per Trade	f	0.06	Allocation fraction of capital
Z-Scale Clamp Range	[min,max]	[0.8, 1.4]	Position size scaling bounds
Timeout Period	$T_{\max}$	60 days	Maximum holding duration