



Cointegration-based pairs trading: identifying and exploiting similar exchange-traded funds

Kezhong Chen¹ · Constantinos Alexiou¹

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Abstract

We examine the effectiveness of pairs trading using ETFs from 2000 to 2024, focusing on how cointegration stability affects profitability and risk. Analyzing 30 ETF pairs with different z-score thresholds, we find that lowering the threshold increases trading opportunities, boosting profits and Sharpe ratios but also raising volatility and drawdowns. Short trading windows, where cointegration holds, limit long-term profitability. While pairs trading captures short-term arbitrage, its success depends on cointegration stability. The study emphasizes the need for adaptive strategies, better pairs selection, and strong risk management for sustained profitability in changing markets.

Keywords Pairs trading · Cointegration · Exchange-traded funds

JEL Classification G10 · G11 · G12

Introduction

Quantitative trading has been widely adopted by hedge funds and investment banks, fundamentally focusing on finding trading signals from a logical or data-driven perspective. Compared to discretionary trading, quantitative trading allows for back testing based on trading rules to determine long-term returns and risks. This automated and systematic approach effectively reduces human errors, hence enhancing the scientific and stable nature of trading decisions.

In this context, pairs trading is a strategy that involves using two assets with historically similar price movements. When this similarity is disrupted due to idiosyncratic reasons, the strategy involves going long on the undervalued asset and shorting the overvalued one, waiting for their price movements to revert to historical similarities. This process is divided into two phases. The first phase is the formation period, during which historically similar price-moving assets are paired over a specific period, while the second phase

is the trading period, during which the price spread of the paired assets is continuously monitored. If a divergence in price movements occurs, trades are executed according to the rules derived from historical data. Pairs trading is not only applicable to the stock market but also to futures, forex, and options markets (see Poon and Granger 2003).

By engaging in pairs trading across different markets and asset classes, investors can further diversify risk and enhance the robustness of their strategies. Additionally, pairs trading can be combined with other quantitative trading strategies, such as momentum and mean reversion, to build more complex and diversified trading portfolios, thereby boosting overall investment returns.

In the field of pairs trading, one of the most seminal papers was published by Gatev et al. (1999) in which, by using daily data from US stocks from 1962 to 1997 and the distance method to pairs stocks, studied the corresponding risk and return characteristics. After accounting for the impact of bid-ask spread fluctuations and asynchronous trading, the strategy produced an annualized excess return of up to 11% with low exposure to systematic risk. More importantly, this result could not be explained by previously recorded reversal returns, shown by Jegadeesh (1990) and Lehmann (1990), or momentum returns, shown by Jegadeesh and Titman (1993).

✉ Constantinos Alexiou
constantinos.alexiou@cranfield.ac.uk

Kezhong Chen
kezhong.chen17@alumni.imperial.ac.uk

¹ Cranfield School of Management, Cranfield University,
Cranfield MK43 0AL, UK



This study is motivated by the rapid growth of exchange-traded funds (ETFs) which has created a dynamic and accessible avenue for investors seeking diversified exposure to various asset classes. However, in a highly competitive market, identifying profitable trading strategies remains a challenge. Pairs trading, a market-neutral strategy that capitalizes on price discrepancies between two historically correlated assets, has gained significant attention. While traditional pairs trading relies on statistical correlation of returns, this paper explores a more robust approach based on cointegration of prices—a technique that captures long-term equilibrium relationships between asset prices.

By applying cointegration to ETF pairs trading, we aim to identify and exploit persistent price deviations between ETFs that track similar underlying assets, offering a systematic method to generate consistent returns in both trending and volatile market conditions. This research contributes to the field by offering a quantitative framework for traders and analysts to optimize risk-adjusted returns in the ever-evolving ETF landscape.

More specifically, this study focuses on evaluating the effectiveness of pairs trading strategies using exchange-traded funds (ETFs) over the period from 2000 to 2024. The objective is to assess how the stability of cointegration relationships between ETF pairs influences the profitability and risk-adjusted returns of these strategies. Cointegration, in a statistical sense, refers to a long-run equilibrium relationship between two or more non-stationary time series such that a specific linear (or ratio) combination of them becomes stationary. In this paper, we use ratio cointegration, which interprets this relationship in terms of relative pricing stability over time. In this direction, the study employs a dataset comprising 30 ETF pairs diversified across multiple asset classes and sectors to ensure a comprehensive analysis. The results will be compared under different z -score thresholds to evaluate the impact of trading signal sensitivity on overall performance.

While the results of this study may align with prior research, the motivation for studying ETFs specifically remains valid. ETFs have unique characteristics that distinguish them from individual stocks, such as their composition (e.g., baskets of securities tracking indices, sectors, or commodities), liquidity dynamics, and the role of authorized participants in maintaining price efficiency. These features could theoretically create different opportunities or challenges for pairs trading strategies compared to individual stocks. As such we provide empirical validation in a new context and offer a systematic approach to understanding the limitations of pairs trading in modern markets.

The rest of the paper is organized as follows: Section “[Theoretical consideration and literature review](#)” presents the theoretical consideration in the area, while section “[Research methodology](#)” elaborates on the research

methodology. Section “[Results](#)” discusses the results, and section “[Concluding remarks](#)” provides some concluding remarks.

Theoretical consideration and literature review

Methodological considerations for ETF Pairs trading

In the realm of pairs trading, various methodologies have been developed to identify tradable asset pairs. These include the distance method, cointegration method, time series analysis, stochastic control, machine learning combined forecasts, copula methods, and principal component analysis (PCA). While each of these approaches offers distinct advantages, their effectiveness can vary significantly when applied to exchange-traded fund (ETF) pairs due to the unique characteristics of ETFs, such as liquidity mechanisms, tracking errors, and trading inefficiencies. This study specifically focuses on the distance and cointegration approaches, as they have been extensively validated in academic research and real-world applications. Extending these traditional stock-based strategies to ETF pairs allows the market to gain novel insights into arbitrage opportunities, price inefficiencies, and market structure dynamics.

Distance approach

The distance method, introduced by Gatev et al. (1999), remains one of the most widely employed techniques in pairs trading. The method identifies stock pairs by minimizing the sum of squared deviations (SSD) of their normalized price series over a formation period. While effective for identifying stocks with similar price movements, its applicability to ETF pairs raises several concerns. ETFs are designed to track underlying indices, which may result in artificial comovement rather than genuine statistical arbitrage opportunities. Additionally, tracking errors and differences in fund compositions may lead to deviations that are not purely stochastic but instead systematic in nature.

The primary advantage of the distance approach lies in its simplicity and model-free nature, which eliminates the risk of misestimating parameters or relying on theoretical assumptions. However, its weakness is evident when applied to ETFs—pairs with historically similar price patterns may not revert during the trading period due to fundamental shifts in index compositions or changes in fund management strategies. Empirical studies (Do and Faff 2010) highlight the decline in pairs trading profitability over time, with fundamental risks, noise-trader risks, and synchronization risks contributing to non-converging pairs. Additionally, while sum of squared deviations (SSD) identifies pairs with the



lowest price variance, such pairs often exhibit reduced price divergence, limiting profitability in ETF trading.

Huck and Afawubo (2015) suggest that cointegration-based methods offer superior performance over distance-based approaches, as they explicitly account for long-term relationships rather than relying purely on historical price movements. When applied to ETF pairs, the limitations of the distance method become even more apparent, given that ETFs, unlike individual stocks, exhibit different degrees of tracking error and may have structurally distinct compositions despite short-term price correlations.

Cointegration approach

The cointegration method, in contrast to the distance method, identifies pairs whose price ratios exhibit mean-reverting behavior over time. Equation (1) represents a cointegrated pair where although $P_{1,t}$ and $P_{2,t}$ are individually non-stationary, and their log ratio is stationary.

$$z_t = \log \left(\frac{P_{1,t}}{P_{2,t}} \right) = \beta_0 + \varepsilon_t, \varepsilon_t \sim I(0) \quad (1)$$

where $P_{1,t}$ and $P_{2,t}$ are the prices of two ETFs at time t ; z_t is the log price ratio or cointegration spread; β_0 is the equilibrium mean; ε_t is the stationary residual or deviation from the mean (mean-reverting); $\varepsilon_t \sim I(0)$ implies the spread is stationary, fulfilling the cointegration condition.

Compared to stocks, ETF pairs are inherently more suitable for cointegration-based strategies, as ETFs track indices, which often share economic linkages, sectoral dependencies, or common risk exposures. Vidyamurthy (2004) emphasizes the advantage of cointegration-based selection in ensuring economic stability in pairs relationships, which is particularly relevant in ETF trading, where price deviations are often driven by macroeconomic factors rather than firm-specific idiosyncrasies.

Empirical research supports the efficacy of cointegration-based selection. Rad et al. (2016) conducted a comprehensive study on US stock markets, demonstrating that cointegration-selected pairs yield more reliable trading signals with significantly higher profitability than those selected through the distance method. More than 98% of convergent trades in their study resulted in positive returns, reinforcing the robustness of the method.

Enhancing signal precision in ETF trading

Lin et al. (2006) propose a refinement to cointegration-based strategies through cointegration coefficient weighting (CCW), which optimizes trade execution by setting predefined thresholds for entry and exit conditions. The advantage of this method in ETF trading lies in its ability to mitigate

false signals arising from short-term price noise and tracking discrepancies. However, its strict criteria may limit trade opportunities, which can be a drawback in low-volatility ETF markets.

Puspaningrum et al. (2010) further refine the cointegration approach by developing an optimization algorithm for setting dynamic trade boundaries. Their findings, based on Australian stock exchange data, validate the profitability of this approach, which could be extended to ETF trading to enhance systematic arbitrage strategies.

Cointegration in futures and spread trading

The concept of cointegration has been extensively studied in futures markets, where it has been shown to be effective in capturing mean-reverting price relationships. Brenner and Kroner (1995) highlight that cointegration is more prominent in spot-forward price relationships in currency markets, a phenomenon also observed in ETF arbitrage, where ETFs and their underlying indices often exhibit stable long-term relationships. Studies by Cohn and Wahab (1994) and Liu and Chou (2003) confirm the profitability of spread trading using cointegration analysis, reinforcing the method's potential for ETF-based arbitrage strategies.

Market-neutral strategies and portfolio optimization

Pairs trading is often utilized as a market-neutral strategy, reducing exposure to systematic market risks. This characteristic is particularly beneficial for ETF trading, where sector-based ETFs or factor-driven funds can be paired to exploit relative mispricing while maintaining neutrality to broader market movements. Studies such as those by Alexander and Dimitriu (2005) demonstrate that cointegration-based methods outperform traditional tracking error minimization techniques, particularly in statistical arbitrage settings. Extending these findings to ETFs could provide investors with robust hedging and alpha-generation strategies.

Statistical considerations in ETF trading

While cointegration-based strategies offer significant advantages, their effectiveness is contingent upon accurate parameter estimation and robustness to market regime shifts. Hakkio and Rush (1991) emphasize that increasing data sampling frequency does not necessarily improve cointegration test accuracy, highlighting the importance of selecting appropriate sampling frequencies for ETF pair selection. Burgess (1999) demonstrates the potential of statistical arbitrage in FTSE 100 stocks, which could be extended to ETF pairs, particularly in high-frequency trading environments.



On the whole, when applied to ETF pairs, traditional stock-based pairs trading methods exhibit varying degrees of efficacy. The distance method, while straightforward, fails to account for structural factors unique to ETFs, such as tracking errors and index composition changes. Cointegration-based strategies, on the other hand, offer a more stable and economically meaningful approach by identifying long-term relationships that persist despite short-term price fluctuations. In this context, two series x_t and y_t are said to be cointegrated if each series is non-stationary and there exists a linear combination of the two series $z_t = ax_t + bx_t$, such that z_t is stationary. When both x_t and y_t however represent asset prices—such as those of two ETFs—the cointegration condition implies that their price relationship is mean-reverting over the long run (see Eq. 1 above).

Extending cointegration-based methods to ETF trading enables the market to exploit arbitrage opportunities more effectively while maintaining market neutrality and reducing exposure to transient price inefficiencies. This study underscores the necessity of adapting existing methodologies to ETF-specific characteristics, ensuring their continued relevance in modern quantitative trading strategies.

Research methodology

The primary objective of the research strategy is to exploit short-term deviations in the price relationship between two cointegrated assets, with the expectation that these deviations will revert to their historical norm, allowing for profitable trades. The methodology consists of several key steps to identify suitable ETF pairs, establish a robust trading signal, and efficiently manage trades to maximize returns while minimizing risk. Each step—from data selection and cointegration testing to signal generation and trade execution—builds upon the previous one to create a cohesive strategy to capitalize on market inefficiencies. This section will detail each component of the methodology, explaining how they work together to achieve the overarching goal of this pair trading strategy.

Data selection

The dataset used in this research spans from 2000 to 2024 and includes 30 pairs of exchange-traded funds (ETFs). These ETFs are diversified across multiple asset classes and sectors, ensuring a broad and balanced representation of the market. The dataset encompasses 5 major asset classes, covering equities, bonds, commodities, real estate, and international markets. The ETFs represent 12 different sectors of the economy, providing exposure to a wide range of industries.

These asset classes and sectors are selected to ensure that the pair trading strategy is robust and diversified, capturing relative performance across various market segments. The specific details of the dataset can be found in Table 1.

Implementation of the trading strategy

The implementation of the pairs trading strategy follows a two-step process: a formation period followed by a trading period.

1. **Formation Period:** The first 12 months of data serve as the formation period, during which the price movements of the ETF pairs are analyzed to establish historical price relationships. This period is essential for calculating key

Table 1: Overview of asset classes and sectors covered by the ETF pairs

Sector/Category	ETF Ticker	ETF Ticker
S&P 500 Index	SPY	IVV
Energy Sector	XLE	VDE
Technology Sector	XLK	VGT
Financial Sector	XLF	VFH
Precious Metals	SLV	GLD
Treasury Bonds	TLT	IEF
Materials Sector	XLB	VAW
Utilities Sector	XLU	VPU
Technology Sector	QQQ	XLK
Real Estate	IYR	VNQ
Healthcare Sector	XLV	VHT
Consumer Discretionary	XLY	VCR
Consumer Staples	XLP	VDC
Small-Cap Stocks	IWM	VTWO
Developed Markets	EFA	VEA
Investment Grade Bonds	LQD	VCIT
High Yield Bonds	HYG	JNK
Emerging Markets	IEMG	VWO
Treasury Bonds	IEF	SHY
Aggregate Bonds	BND	AGG
Total Stock Market	VTI	SCHB
Large-Cap Stocks	IWB	VV
Metals & Mining	XME	PICK
Biotechnology	XBI	IBB
Information Technology	FTEC	XLK
Mid-Cap Stocks	VO	IJH
Factor Investing	MTUM	QUAL
Retail & Consumer Services	XRT	IYC
International Markets	VEU	IEFA
Emerging Markets Bonds	EMB	PCY

Asset classes and sectors covered by the 30 ETF pairs used in the study. Each pair is listed with its corresponding sector or category and the specific ETFs representing those sectors.



parameters, such as the mean and standard deviation of the price spread, which guide the trading strategy.

2. **Trading Period:** After the formation period, a dynamic trading approach is employed. Each month, the validity of the ETF pairs is reassessed using the most recent 12 months of data. If the statistical relationship that justified the pair continues to hold, the trading period is extended. If not, the trading period for that pair ends. This approach ensures that trades are based on current market conditions, making the strategy more adaptive and reliable compared to a fixed trading period.

This dynamic method, differing from the fixed-period strategy used by Rad et al. (2016), aims to enhance the effectiveness and flexibility of the pairs trading strategy, reducing the risk of making trades based on outdated or invalidated assumptions.

Pairs trading strategy framework based on price ratio method

In ETF pairs trading strategies, the detection of cointegration relationships and the generation of trading signals are critical to the success of the strategy. Given the stability and computational efficiency of the price relationship between ETFs, we adopt the price ratio method to detect cointegration and generate trading signals through the calculation of the Z-Score. Further down we describe the price ratio method, which optimizes the parameters for opening and closing positions, and explain the rationale behind these parameter choices.

Rad et al. (2016) use a dynamic weight allocation method based on cointegration, where the investment in a pair is proportionate to the cointegration coefficient, reflecting the underlying economic relationship between the assets. This contrasts with our approach, which employs equal capital allocation and equal share numbers across assets. Our method emphasizes simplicity, ensuring consistent risk distribution and easier portfolio management. While Rad et al.'s (2016) approach may yield higher returns if the cointegration relationship holds, our approach reduces complexity and model risk, hence providing more stable returns across varying market conditions.

Theoretical basis of the price ratio method

Assume we have two time series $X_{1,t}$ and $X_{2,t}$, representing the prices of two ETFs. We calculate the price ratio between the two ETFs, Price Ratio_t , to detect if a cointegration relationship exists:

$$\text{Price Ratio}_t = \frac{X_{1,t}}{X_{2,t}} \quad (2)$$

If the price ratio deviates from its long-term mean in the short term and is stationary, it suggests a cointegration relationship between the two ETFs. This deviation can then be used to generate buy and sell signals for profit.

To determine whether the Price Ratio_t is stationary, we use the standard Augmented Dickey-Fuller (ADF) test. Given the volume of data and the need for dynamic analysis, the ADF test was conducted monthly for each pair of ETFs. Therefore, detailed tables of the results are not included here. Once stationarity of the price ratio is confirmed, we compute the rolling mean and standard deviation of the ratio and quantify its deviation using the Z-score:

Rolling Mean and Standard Deviation:

$$\mu_t = \frac{1}{n} \sum_{i=0}^{n-1} \text{Price Ratio}_{t-i} \quad (3)$$

$$\sigma_t = \sqrt{\frac{1}{n} \sum_{i=0}^{n-1} (\text{Price Ratio}_{t-i} - \mu_t)^2} \quad (4)$$

Z-Score Calculation:

$$\text{Z Score}_t = \frac{\text{Price Ratio}_t - \mu_t}{\sigma_t} \quad (5)$$

Signal Generation:

Opening Signal:

- When $\text{Z Score}_t > 2$, the price ratio is significantly high, suggesting a sell short signal on ETF1 and a buy signal on ETF2.
- When $\text{Z Score}_t < -2$, the price ratio is significantly low, suggesting a buy signal on ETF1 and a sell short signal on ETF2.

Closing Signal:

Based on empirical findings by Avellaneda and Lee (2010), the thresholds for closing positions are set as follows:

- Close short positions when Z Score_t falls to above 0.75 after being high.
- Close long positions when Z Score_t rises to below -0.5 after being low.

Share number selection is crucial for risk management and capital allocation. We propose two different methods for calculating share numbers:

Method 1: Equal share number In this method, we assume the same number of shares for buying and selling ETFs, ensuring simplicity and consistency in execution. The calculation is as follows:

- Total Investment Amount: Assume the target total investment amount for each ETF pairs is \$1 million.
- Share Number Calculation:

$$\text{Contract Number} = \frac{1000,000}{P_1 + P_2} \quad (6)$$

where P_1 and P_2 are the prices of ETF1 and ETF2, respectively, and the floor function ensures that the share number is an integer.

Execution Logic: Buy and sell the calculated equal number of shares for ETF1 and ETF2.

Method 2: Equal capital allocation In this method, we ensure that each ETF receives equal investment capital, meaning the total investment of \$1 million is split evenly between the two ETFs. The calculation is as follows:

- Investment Amount per ETF: Each ETF is allocated \$500,000.
- Share Number Calculation:

$$\text{Share Number1} = \frac{500,000}{P_1} \quad (7)$$

$$\text{Share Number2} = \frac{500,000}{P_2} \quad (8)$$

where Share Number1 and Share Number2 are the share numbers for ETF1 and ETF2, respectively, and P_1 and P_2 are their prices. The floor function ensures that the share numbers are integers.

Execution Logic: The number of shares bought or sold is based on the respective prices and target capital, so the share numbers may differ, but the investment amount in each ETF is equal.

Strategy execution and PnL calculation Based on the generated trading signals and the selected share number method, trades are executed daily, and the Profit and Loss (PnL) is calculated:

Method 1: Equal Share Number:

$$PnL_t = (\Delta P_1 - \Delta P_2) * \text{Contract Number} \quad (9)$$

Method 2: Equal Capital Allocation:

$$PnL_t = (\Delta P_1 * \text{Contract Number1}) - (\Delta P_2 * \text{Contract Number2}) \quad (10)$$

where ΔP_1 and ΔP_2 represent the daily price changes of ETF1 and ETF2, respectively.

The two methods allow the strategy to flexibly adjust the share number based on different capital allocation needs and risk management preferences, enabling more precise capital management and profit maximization.

Performance indicators applied

Total return is the most straightforward measure of a strategy's success. It calculates the overall percentage gain or loss from the initial capital over the investment period. It reflects the absolute performance of the strategy and answers the fundamental question: "How much money did we make?"

$$\text{Total Return (\%)} = \left(\frac{\text{Final Asset Value} - \text{Initial Capital}}{\text{initial Capital}} \right) * 100 \quad (11)$$

Final Asset Value is the value of the portfolio at the end of the period; Initial Capital is the starting amount of money invested.

Sharpe ratio The Sharpe ratio is used to evaluate the risk-adjusted return of a strategy. It measures how much excess return you are receiving for the extra volatility that you endure for holding a riskier asset. A higher Sharpe ratio indicates better risk-adjusted performance. For simplicity and in line with common practice, we assume that the risk-free rate is 0, which means we are not subtracting a risk-free return from the strategy's return when calculating the Sharpe ratio.

$$\text{Sharpe Ratio} = \frac{\text{Mean Daily Return}}{\text{Standard Deviation of Daily Returns}} * \sqrt{252} \quad (12)$$

Mean Daily Return is the average daily return of the portfolio; Standard Deviation of Daily Returns represents the portfolio's volatility; 252 is the number of trading days per year.

Maximum drawdown and recovery time Maximum Drawdown (MDD) measures the largest peak-to-trough decline during the investment period. It is crucial because it helps assess the risk of catastrophic losses in the strategy, showing the worst-case scenario of loss an investor could face before a new peak is achieved.

$$\text{Maximum Drawdown (\%)} = \min \left(\frac{\text{Asset Value}_t - \text{Rolling Max Asset Value}}{\text{Rolling Max Asset Value}} \right) \quad (13)$$

$$\begin{aligned} &\text{Max Drawdown Recovery Time} \\ &= \frac{\text{max (End Date of Recovery)} - \text{Start Date of Recovery}}{\text{365}} \end{aligned} \quad (14)$$

Asset Value_{*t*} is the asset value at time *t*; Rolling Max Asset Value is the maximum asset value achieved before time *t*; Start Date of Drawdown is when the drawdown begins; End Date of Recovery is when the asset value recovers to the previous peak.

Average drawdown recovery time Average Drawdown Recovery Time measures how long, on average, it takes for the strategy to recover from drawdowns. It is important because it provides insight into the resilience of the strategy—how quickly it can rebound after losses.

$$\text{Average Drawdown Recovery Time} = \frac{1}{N} \sum_{i=1}^N \frac{\text{End Date of Recovery} - \text{Start Date of Recovery}}{365} \quad (15)$$

Start Date of Drawdown and End Date of Recovery are defined as above; *N* is the number of drawdown periods.

Correlation with SPY Correlation with S&P 500 measures the degree to which the returns of the strategy move about the returns of the market movements. A low or negative correlation suggests that the strategy might be less dependent on market conditions, potentially offering diversification benefits.

$$\text{Correlation with SP500} = \frac{\text{Cov}(\text{Strategy Daily Returns}, \text{SP500 Daily Returns})}{\sigma_{\text{Strategy}} * \sigma_{\text{SP500}}} \quad (16)$$

Mean Daily Return is the average daily return of the portfolio; Standard Deviation of Daily Returns represents the portfolio's volatility.

Data

Table 2 provides a comparison of two trading strategies—"equal share" and "equal capital"—across various *z*-score thresholds. Key observations include that both strategies generally show positive returns, with statistically significant results, particularly as the *z*-score decreases. The "equal capital" strategy demonstrates stronger statistical significance (higher *t*-statistics) at lower *z*-scores, indicating more consistent profitability. However, both strategies exhibit high kurtosis, pointing to the presence of extreme values or outliers in the PnL distributions, which suggests potential risks

associated with rare but significant losses. Overall, the table

highlights that while the strategies can be profitable, they

also carry substantial tail risk.

Table 2 Statistics of PnL in %

	Mean	<i>t</i> -stat	Std. Dev	Skewness	Kurtosis	Var (95%)	CVaR (95%)	JB Test <i>p</i> value
<i>Strategy (equal share)</i>								
<i>z</i> -score = 2	0.00006	1.36	0.0002	−0.9623	19.8658	−0.0002	−0.0004	0
<i>z</i> -score = 1.8	0.00009	2.23**	0.0002	−0.5383	17.1256	−0.0002	−0.0004	0
<i>z</i> -score = 1.6	0.00008	1.94*	0.0002	−0.2080	11.4572	−0.0003	−0.0005	0
<i>z</i> -score = 1.4	0.00001	2.57**	0.0002	0.0459	10.5552	−0.0003	−0.0005	0
<i>z</i> -score = 1.2	0.00001	2.74***	0.0002	−0.5232	18.9875	−0.0003	−0.0005	0
<i>Strategy (equal capital)</i>								
<i>z</i> -score = 2	0.00005	2.19**	0.0001	−0.1482	14.3300	−0.0001	−0.0002	0
<i>z</i> -score = 1.8	0.00005	2.34**	0.0001	0.1673	13.2538	−0.0001	−0.0002	0
<i>z</i> -score = 1.6	0.00005	2.78***	0.0001	0.2282	12.5408	−0.0001	−0.0002	0
<i>z</i> -score = 1.4	0.00006	3.19***	0.0001	0.4052	13.7619	−0.0001	−0.0002	0
<i>z</i> -score = 1.2	0.00007	4.23***	0.0001	0.6853	14.0048	−0.0001	−0.0002	0

***Significant at 1% level; **significant at 5% level; *significant at 10% level



Data source analysis

During the analysis of the data, several noteworthy observations and perspectives emerged. Firstly, while all ETF pairs exhibited similar historical trends between 2000 and 2024, indicating a strong correlation in their overall market movement, this consistency in historical trends does not necessarily imply a long-term cointegrated relationship. Among all ETF pairs, the most representative example is SPY (SPDR S&P 500 ETF) and IVV (iShares Core S&P 500 ETF). As shown in Fig. 1, in appendix, these two ETFs have maintained a cointegrated relationship for 24 years under the Johansen cointegration test as defined by the Engle-Granger 2-Step method. The frequent spikes observed in the price ratio curve indicate short-term deviations from the mean, which represent potential trading opportunities. Based on the historical price trends alone, SPY and IVV appear to be ideal targets for pairs trading.

However, this study's findings resonate with those of Do and Faff (2012), who highlighted that while some pairs may exhibit stable cointegration, most pairs experience transient relationships that are often dependent on specific market conditions. This transient nature was observed in pairs like QQQ (Invesco QQQ Trust) and XLK (Technology Select Sector SPDR Fund) in Fig. 2, in appendix, although highly correlated, did not achieve stationarity over the 24 years. Their price ratio consistently hovered around 2, but this was not sufficient to establish a reliable cointegration, and only brief periods made them suitable for pairs trading. This suggests that the presence of a cointegrated relationship is not a universal phenomenon but is highly dependent on the prevailing market conditions.

The randomness of cointegration significantly affects the operability of pair trading. Traditional pairs trading strategies, such as those discussed by Gatev et al. (1999), rely on a stable cointegrated relationship between two assets to conduct arbitrage operations when the price spread widens or narrows. However, when cointegration is random and unstable, as observed in many of the ETF pairs studied, the effectiveness of such strategies is greatly diminished. Traders find it challenging to predict the duration of a cointegrated relationship, thereby increasing trading risks. This aligns with the findings of Huck and Afawubo (2015), who noted that the unpredictability of cointegration often leads to increased risk and reduced profitability, especially when the relationship breaks down suddenly.

Moreover, this fragile cointegration not only shortens the effective trading window for pairs trading but also increases the uncertainty in the decision-making process for traders. When a cointegrated relationship is broken, traders may be unable to adjust their strategies promptly, leading to potential losses. This uncertainty has a more pronounced negative impact on trading outcomes, especially during periods of

significant market volatility, which is consistent with the observations of Rad et al. (2016). Their research highlighted those modern financial markets, with their increased complexity and rapid shifts, pose significant challenges to maintaining the effectiveness of traditional pair trading strategies. Cointegration however remains a valid and widely used technique for identifying long-run price relationships¹.

Despite these challenges, it is worth mentioning that the Price Ratio Approach, when used as a simplified alternative to the Engle-Granger 2-Step method, shows a surprising degree of similarity in actual testing. Specifically, the spreads derived from both the Price Ratio Approach and the Engle-Granger 2-Step method exhibit highly consistent patterns. This finding aligns with Vidyamurthy (2004), who emphasized that simpler, more computationally efficient methods could still capture the essence of cointegration relationships effectively. As shown in Fig. 3, in appendix, the four subplots, respectively, display the price trends, price ratio, simple spread (calculated as Price A–Price B), and the spread derived from the Engle-Granger 2-Step method. The near-identical behavior of these methods suggests that, in practice, the simpler Price Ratio Approach can be just as effective in identifying potential trading opportunities, particularly when cointegration relationships exist and are relatively stable.

Table 3 in the results section further supports this analysis by providing detailed performance metrics for various ETF pairs, revealing that while some pairs, like SPY_IVV, exhibited strong returns and stability, others, like QQQ_XLK, struggled to maintain consistent performance. The variability in outcomes across different pairs underscores the importance of carefully selecting pairs with strong, stable cointegration relationships, as discussed in the literature. It also highlights the limitations of relying solely on historical correlations without considering the underlying market conditions that may influence these relationships over time.

Results

Performance analysis

Portfolio with equal share number

The portfolio employing a z-score threshold of 2 and equal share numbers yielded a modest total profit of 1.01% and a Sharpe ratio of 0.28. This relatively low risk-adjusted return

¹ Instead of attempting to predict whether a pair will remain cointegrated, which is indeed uncertain, our strategy takes a more pragmatic approach: we assume that if two ETFs appear cointegrated over the past 200 trading days, they are likely to remain so in the following month. This is a working assumption that is re-evaluated on a rolling basis.



Table 3 Detailed performance (equal share)

Ticker	Total Profit in %	Sharpe Ratio	Maximum Drawdown	Average Drawdown Recovery Time	Max Drawdown Recovery Time	Correlation with SPY
SPY_IVV	29.1043	1.5351	−0.0131	0.0233	0.3288	0.0760
XLE_VDE	1.2295	0.1208	−0.0152	1.1775	5.6438	−0.0105
XLK_VGT	6.4774	0.4805	−0.0098	3.3836	9.8466	−0.0198
XLF_VFH	−1.6726	−0.0870	−0.0579	5.5543	16.4247	0.0288
SLV_GLD	−0.1122	−0.0041	−0.0297	16.3781	16.3781	0.0019
TLT_IEF	0.0000		0.0000			
XLB_VAW	7.7510	0.4481	−0.0134	1.0039	4.6849	−0.0412
XLU_VPU	11.2900	0.3800	−0.0304	1.8161	7.6000	−0.0041
QQQ_XLK	−10.2451	−0.3462	−0.1116	21.8055	21.8055	−0.0917
IYR_VNQ	2.8486	0.2767	−0.0112	1.0806	9.9973	0.0370
XLV_VHT	0.3063	0.0256	−0.0170	5.4712	10.5288	−0.0820
XLY_VCR	−3.9154	−0.3038	−0.0392	12.2356	12.2356	−0.0584
XLP_VDC	−1.4869	−0.0619	−0.0414	15.1370	15.1370	0.0977
IWM_VTWO	−15.5973	−0.2979	−0.1965	2.0000	3.7973	0.0845
EFA_VEA	−3.4444	−0.2195	−0.0511	3.2438	8.0000	0.0507
LQD_VCIT	−0.9945	−0.2209	−0.0139	6.1288	12.2548	0.0121
HYG_JNK	1.5979	0.5238	−0.0008	1.4971	4.1534	0.0122
IEMG_VWO	−1.5133	−0.1892	−0.0235	8.2548	8.2548	0.0090
IEF_SHY	−2.8808	−0.3104	−0.0327	15.1014	15.1014	0.0779
BND_AGG	1.5201	0.1860	−0.0070	1.0042	5.9918	0.0729
VTI_SCHB	22.4735	0.4571	−0.0586	0.4325	3.5014	−0.0246
IWB_VV	−0.3590	−0.0258	−0.0263	18.7370	18.7370	0.0014
XME_PICK	−11.4161	−0.4241	−0.1147	10.0219	10.0219	0.0094
XBI_IBB	0.1041	0.0520	−0.0017	6.3959	12.5863	0.0118
FTEC_XLK	−0.7770	−0.1364	−0.0148	1.9904	7.9425	−0.0527
VO_IJH	2.9756	0.0879	−0.1224	2.6301	9.5562	0.0563
MTUM_QUAL	−0.6682	−0.2400	−0.0067	7.5096	7.5096	0.0208
XRT_IYC	−1.8565	−0.1444	−0.0299	5.3000	10.5918	0.0015
VEU_IEFA	−1.0854	−0.2148	−0.0116	1.7356	3.4438	0.0124
EMB_PCY	0.5096	0.0408	−0.0189	2.5951	9.5534	0.0171

Metrics of Various ETF Pairs, Including Total Profit, Sharpe Ratio, Maximum Drawdown, Recovery Times (Measured in Years), and Correlation with SPY, Spanning the Period from 2000 to 2024.

aligns with the findings of Rad et al. (2016), who observed a decline in the profitability of pairs trading strategies over time. The high proportion of pairs with few trades, as observed in this study, further supports the concerns raised by Huck and Afawubo (2015) regarding the limited practical application of these strategies due to infrequent trading opportunities.

Despite the strategy's low maximum drawdown of −1.02%, the lengthy recovery time of up to 5.01 years indicates that while the strategy was relatively safe from catastrophic losses, it struggled to generate significant returns promptly. This performance mirrors the historical observations by Gatev et al. (1999), who noted that while pair trading can produce stable returns, it often fails to capitalize on rapid market movements due to its reliance on mean

reversion, which may not always occur within the expected timeframe.

The chart in Fig. 4, in appendix, illustrates the performance of a portfolio consisting of 30 ETF pairs over 24 years, using a z-score of 2 as the trading threshold. The strategy involved equally numbered long and short positions in each ETF pair, with no transaction costs considered. The total profit achieved by the portfolio, a modest 1.01% over such a long duration, suggests that while the strategy remained in positive territory, it did not generate significant returns.

The portfolio's Sharpe ratio of 0.28 further underscores the low level of risk-adjusted return. One contributing factor to this low Sharpe ratio is the use of the threshold proposed by Avellaneda and Lee (2010). Although this empirical

Table 4 Detailed performance (equal capital allocation)

Ticker	Total Profit in %	Sharpe Ratio	Maximum Drawdown	Average Drawdown Recovery Time	Max Drawdown Recovery Time	Correlation with SPY
SPY_IVV	28.9660	1.5300	1.5300	−0.0138	−0.0138	0.0233
XLE_VDE	0.5237	0.0997	0.0997	−0.0079	−0.0079	1.9279
XLK_VGT	2.2349	0.3327	0.3327	−0.0050	−0.0050	2.6822
XLF_VFH	2.3118	0.2528	0.2528	−0.0188	−0.0188	3.9078
SLV_GLD	−4.9044	−0.3062	−0.3062	−0.0490	−0.0490	16.3808
TLT_IEF	0.0000			0.0000	0.0000	
XLB_VAW	0.3319	0.0944	0.0944	−0.0053	−0.0053	2.7425
XLU_VPU	7.6353	0.5985	0.5985	−0.0056	−0.0056	0.6691
QQQ_XLK	−5.6317	−0.4577	−0.4577	−0.0589	−0.0589	21.8055
IYR_VNQ	2.3911	0.2278	0.2278	−0.0128	−0.0128	1.6517
XLV_VHT	−0.8558	−0.3410	−0.3410	−0.0098	−0.0098	16.4356
XLY_VCR	−1.2073	−0.3175	−0.3175	−0.0137	−0.0137	1.8137
XLP_VDC	−2.0859	−0.4343	−0.4343	−0.0209	−0.0209	15.1370
IWM_VTWO	4.0573	0.7743	0.7743	−0.0020	−0.0020	0.2265
EFA_VEA	2.7737	0.3302	0.3302	−0.0066	−0.0066	0.6857
LQD_VCIT	−0.7348	−0.2050	−0.2050	−0.0106	−0.0106	12.2658
HYG_JNK	1.5808	0.5798	0.5798	−0.0010	−0.0010	0.3470
IEMG_VWO	−0.9271	−0.1406	−0.1406	−0.0144	−0.0144	8.2521
IEF_SHY	−2.6467	−0.3170	−0.3170	−0.0302	−0.0302	15.1014
BND_AGG	1.9974	0.2640	0.2640	−0.0063	−0.0063	1.1696
VTI_SCHB	8.2214	1.0588	1.0588	−0.0045	−0.0045	0.1000
IWB_VV	0.2262	0.0209	0.0209	−0.0249	−0.0249	6.0840
XME_PICK	−10.9499	−0.4021	−0.4021	−0.1137	−0.1137	10.0219
XBI_IBB	0.3077	0.1671	0.1671	−0.0019	−0.0019	0.2055
FTEC_XLK	−1.4397	−0.5156	−0.5156	−0.0145	−0.0145	7.9836
VO_IJH	−2.0680	−0.2854	−0.2854	−0.0218	−0.0218	18.2959
MTUM_QUAL	−0.5144	−0.1493	−0.1493	−0.0054	−0.0054	7.5096
XRT_IYC	−1.6223	−0.1291	−0.1291	−0.0278	−0.0278	5.3000
VEU_IEFA	−1.2047	−0.2666	−0.2666	−0.0120	−0.0120	3.4822
EMB_PCY	−2.6151	−0.3976	−0.3976	−0.0272	−0.0272	13.0301

Metrics of Various ETF Pairs, Including Total Profit, Sharpe Ratio, Maximum Drawdown, Recovery Times (Measured in Years), and Correlation with SPY, Spanning the Period from 2000 to 2024.

threshold may be effective for other assets, it appears less suitable for ETF pairs in this context. Notably, 18 out of the 30 ETF pairs had fewer than 10 trades over the entire 24-year period. As a result, a substantial portion of the capital was tied up in positions with little to no trading activity, which significantly dragged down the portfolio's overall performance. This lack of trading activity across a large portion of the portfolio meant that the potential benefits of diversification were not fully realized.

The portfolio's maximum drawdown of −1.02% represents the worst peak-to-trough decline in value. Although this drawdown is relatively shallow, the recovery time from the maximum drawdown was notably long, taking up to 5.01 years to fully recover. This prolonged recovery period indicates that the portfolio encountered significant setbacks,

reducing its attractiveness as a reliable long-term trading strategy. In contrast, Rad et al. (2016)'s strategy, which achieved a Sharpe ratio of 0.6969, experienced a deeper maximum drawdown of 4.59%, but its overall risk-adjusted performance was superior.

The portfolio's average drawdown recovery time is 0.25 years, or roughly three months, suggesting that it generally recovered from losses relatively quickly. However, the one significant drawdown extending over five years indicates that certain market conditions posed considerable challenges to the strategy.

Furthermore, the portfolio's correlation with the SPY (S&P 500 ETF) is 0.05, indicating that its performance was largely uncorrelated with broader market movements. Despite this low correlation, which typically suggests

diversification benefits, the portfolio's inefficiencies meant that these benefits were not fully capitalized on.

Table 4 provides a comprehensive view of the performance of various ETF pairs, each showcasing distinct characteristics in terms of profitability, risk, and market correlation. The significant variation in performance metrics across the pairs offers valuable insights into the potential strengths and weaknesses of different pairs trading strategies over a long-term horizon.

Starting with the top performer, the SPY_IVV pair generated a substantial total profit of 29.10%, paired with a high Sharpe ratio of 1.5351. This indicates that the pair provided strong returns relative to the risk assumed. Notably, the maximum drawdown of -1.31% was minimal, and the quick recovery times—both average and maximum—highlight the pair's resilience. The average recovery time of just 0.0233 years (approximately 8.5 days) and a maximum recovery time of 0.3288 years (about 4 months) underscore the stability and reliability of this pair as an investment vehicle. Its low correlation with SPY (0.076) further suggests that it could serve as an effective diversification tool in a broader portfolio.

In stark contrast, the QQQ_XLK pair stands out as one of the worst performers, with a total profit of -10.25% and a negative Sharpe ratio of -0.3462 . The extremely long maximum drawdown recovery time of 21.81 years suggests that once this pair experienced a significant downturn, it took almost the entire period to recover, making it an unattractive option for investors seeking quicker returns or more stable investments. This prolonged recovery, combined with a high maximum drawdown of -11.16% , indicates that this pair was highly volatile and prone to extended periods of underperformance, which could erode investor confidence.

Similarly, XME_PICK also displayed poor performance metrics, with a total profit of -11.42% and a Sharpe ratio of -0.4241 . The maximum drawdown of -11.47% and a lengthy recovery time of 10.02 years reflect the significant risks associated with this pair. These figures suggest that any gains made by this pair were quickly overshadowed by severe losses, leading to a substantial erosion of value over time.

Pairs like XLE_VDE and XLK_VGT, while managing to stay in positive territory, did so with considerable limitations. XLE_VDE's total profit of 1.23% and Sharpe ratio of 0.1208, coupled with a maximum drawdown of -1.52% and a long recovery period of 5.64 years, indicate that while this pair avoided significant losses, it also struggled to generate meaningful returns. XLK_VGT performed slightly better, with a total profit of 6.48% and a Sharpe ratio of 0.4805, but its extended recovery time of 9.85 years indicates that the pair suffered from prolonged periods of underperformance, which could have been challenging for investors to endure.

Some pairs, such as SLV_GLD and XLF_VFH, performed poorly with negative returns and negative Sharpe ratios, suggesting that these pairs were not suitable for a risk-averse investor. SLV_GLD had a small negative total profit of -0.11% and a near-zero Sharpe ratio of -0.0041 , with a maximum drawdown of -2.97% and an exceptionally long recovery time of 16.38 years. This performance indicates that the pair was not only unprofitable but also highly volatile, with significant downside risk and little to no compensating return. XLF_VFH, with a total profit of -1.67% and a Sharpe ratio of -0.0870 , exhibited similar issues, compounded by a significant maximum drawdown of -5.79% and a recovery time of over 16 years, making it one of the least appealing pairs in the dataset.

Conversely, some pairs like HYG_JNK and BND_AGG showed moderate, yet stable, performance. HYG_JNK's total profit of 1.60% and Sharpe ratio of 0.5238 indicate a reasonable balance between risk and return. The pair's maximum drawdown of -0.078% was very low, and it recovered quickly, with average and maximum recovery times of 1.50 and 4.15 years, respectively. BND_AGG, with a total profit of 1.52% and a Sharpe ratio of 0.1860, also demonstrated a balanced profile, with a maximum drawdown of -0.70% and a relatively quick recovery, highlighting the pair's potential as a safer, though not highly profitable, investment.

The TLT_IEF pair, which shows zero values in several key metrics, is an interesting case. The lack of performance data for this pair is likely due to the chosen z -score threshold of 2 being too stringent, resulting in very few or no trading signals being generated over the analyzed period. Essentially, the z -score threshold was set so high that the conditions required to initiate trades were rarely, if ever, met. As a result, the strategy did not engage in any trades for this pair, leading to the absence of returns and other related performance metrics.

Finally, pairs like VTI_SCHB, which delivered a total profit of 22.47% and a Sharpe ratio of 0.4571, appear relatively strong on paper. However, the maximum drawdown of -5.86% and a short recovery time of 3.5 years suggest that while the pair experienced some volatility, it managed to recover relatively quickly, making it a potentially viable option for investors seeking moderate returns with manageable risk.

Portfolio with equal amount of asset allocation

The analysis of portfolio performance using different allocation strategies reveals a nuanced trade-off between total profit and risk-adjusted returns. When applying the equal capital allocation approach, the portfolio achieved a total profit of 0.81%, accompanied by a higher Sharpe ratio of 0.45. This result aligns with the findings of Alexander and Dimitriu (2005), who noted that cointegration-based



strategies often balance higher Sharpe ratios against lower total profits. Additionally, the lower maximum drawdown of -0.36% suggests that the equal capital allocation approach effectively mitigates risk. However, the extended recovery time of 11.01 years indicates potential challenges in volatile market conditions, highlighting the need for dynamic risk management.

The modest improvements in risk-adjusted returns suggest that equal capital allocation may offer better downside protection compared to equal share allocation, especially in low-volatility markets. Nevertheless, the longer recovery time emphasizes the importance of adapting risk management strategies to changing market environments, as static allocation methods may not be sufficient.

In support of these findings, Fig. 5, in appendix, presents the performance metrics for a portfolio consisting of 30 ETF pairs, each with equal value positions of \$500,000 in both long and short trades, using a z -score of 2 as the trading threshold. The analysis confirms that the portfolio achieved a total profit of 0.81%, with a Sharpe ratio of 0.45, indicating moderate risk-adjusted returns. The maximum drawdown was -0.36% , with an average drawdown recovery time of 0.36 years (approximately 4.3 months). However, the maximum drawdown recovery time was notably lengthy at 11.01 years, suggesting significant difficulty in recovering from the portfolio's deepest losses. The portfolio also exhibited a low correlation with SPY, at 0.08, indicating limited exposure to broader market movements.

When compared to an alternative strategy where position sizes were determined by holding equal quantities of each ETF (i.e., one A for one B), several key differences emerge. In the equal quantity scenario, the portfolio generated a slightly higher total profit of 1.01%, but this was accompanied by a lower Sharpe ratio of 0.28. This suggests that while the equal quantity strategy produced more profit, it did so with less efficiency in terms of risk-adjusted returns.

Moreover, the maximum drawdown in the equal quantity strategy was significantly larger at -1.02% , compared to -0.36% in the equal value strategy, indicating greater potential losses. Despite this, the average drawdown recovery time was shorter at 0.25 years, and the maximum recovery time was 5.01 years, considerably less than the 11.01 years observed in the equal value strategy. This suggests that while the equal quantity approach resulted in more severe drawdowns, it allowed for quicker recovery from these losses.

In terms of correlation with SPY, the equal quantity strategy had a slightly lower correlation of 0.05, compared to 0.08 in the equal value strategy, indicating marginally better diversification benefits and reduced correlation with the overall market. The detailed performance can be seen in Table 4.

Performance after reducing Z -score to 1.5

Lowering the z -score threshold to 1.5 in the pair trading strategy significantly increased trading opportunities, leading to higher total profits in both the equal share (1.85%) and equal capital (1.23%) approaches (see Tables 5 and 6). These results align with Vidyamurthy (2004), who advocated for more sensitive trading thresholds to capture a greater number of profitable trades. However, this adjustment also introduced greater volatility. In the equal share approach, the maximum drawdown deepened to -1.82% , while in the equal capital approach, it slightly increased to -0.41% . This highlights the inherent trade-offs in pairs trading strategies, where increased sensitivity to trading signals can lead to higher returns but also greater exposure to market noise and risk.

The shortening of the average drawdown recovery time in the equal share approach from 0.25 to 0.16 years suggests that the strategy became more responsive, recovering from losses more quickly. However, in the equal capital approach, the maximum drawdown recovery time extended from 7.23 to 11.01 years, indicating that, despite improved profitability, the strategy could still be vulnerable to prolonged periods of underperformance. These findings emphasize the need for adaptive risk management strategies that can dynamically adjust to changing market conditions, a point also highlighted Do and Faff (2012), who noted that increased trading frequency can exacerbate the impact of market volatility.

Specifically, lowering the z -score threshold from 2 to 1.5 in the equal share approach resulted in an increase in total profit from 1.01 to 1.85%, with a slight improvement in the Sharpe ratio from 0.28 to 0.37. However, this came at the cost of a deeper maximum drawdown, which increased from -1.02% to -1.82% . Despite the larger drawdowns, the portfolio recovered more quickly, as indicated by the reduction in both average and maximum drawdown recovery times—from 0.25 to 0.16 years and from 5.01 to 3.82 years, respectively. The correlation with SPY rose slightly from 0.05 to 0.08, maintaining low market exposure.

In contrast, the equal capital approach saw a total profit increase from 0.81 to 1.23%, with a notable improvement in the Sharpe ratio from 0.45 to 0.54. The maximum drawdown remained modest, increasing only slightly from -0.36% to -0.41% . The average drawdown recovery time decreased from 0.36 to 0.26 years, but the maximum drawdown recovery time extended significantly from 7.23 to 11.01 years, indicating a longer recovery period from its deepest losses. The correlation with SPY slightly decreased from 0.08 to 0.07, suggesting marginally better diversification.

Overall, the primary takeaway is that lowering the z -score threshold indeed uncovered more trading opportunities, leading to higher total profits and improved Sharpe ratios in



Table 5 Detailed performance with lower Z-score at 1.5 (equal share)

Ticker	Total Profit in %	Sharpe Ratio	Maximum Drawdown	Average Drawdown Recovery Time	Max Drawdown Recovery Time	Correlation with SPY
SPY_IVV	35.68763	1.76806	−0.01244	0.03705	0.71781	0.03792
XLE_VDE	1.36574	0.10099	−0.01570	1.44992	11.58630	0.01617
XLK_VGT	11.07159	0.44923	−0.02277	1.01616	9.84658	−0.03259
XLF_VFH	5.49897	0.19730	−0.04517	1.34338	11.57260	−0.00279
SLV_GLD	0.60516	0.02952	−0.04354	5.37717	8.13973	0.03237
TLT_IEF	0.44518	0.12230	−0.00397	1.76438	5.26575	−0.01037
XLB_VAW	9.30818	0.31049	−0.02399	0.78337	3.11781	−0.07725
XLU_VPU	16.74060	0.38182	−0.05070	1.03368	14.82192	0.01087
QQQ_XLK	−4.87884	−0.12119	−0.08793	4.36329	16.29041	−0.10762
IYR_VNQ	6.09729	0.44449	−0.01113	0.71723	5.79726	0.00728
XLV_VHT	1.04111	0.06709	−0.03069	1.99075	10.50959	−0.07519
XLY_VCR	−2.51818	−0.13326	−0.05435	1.06210	3.61096	0.00927
XLP_VDC	−3.01895	−0.09043	−0.07356	7.56986	15.13151	0.16439
IWM_VTWO	−16.23790	−0.25645	−0.24581	1.61781	3.82192	0.09009
EFA_VEA	0.46627	0.02930	−0.03081	1.34599	3.49041	0.05449
LQD_VCIT	−2.80384	−0.38057	−0.03609	6.12877	12.25479	0.00656
HYG_JNK	0.85604	0.15213	−0.01310	1.94012	11.64658	0.00378
IEMG_VWO	−1.92981	−0.21987	−0.02727	8.26575	8.26575	0.00939
IEF_SHY	−3.22448	−0.27611	−0.03574	15.11507	15.11507	0.11544
BND_AGG	1.50881	0.16368	−0.00968	1.16881	5.55342	0.08426
VTI_SCHB	17.62053	0.27229	−0.12935	0.46971	4.51781	0.02002
IWB_VV	0.49387	0.03657	−0.02818	18.73699	18.73699	0.03569
XME_PICK	−12.84150	−0.36418	−0.12841	10.03288	10.03288	0.00624
XBI_IBB	0.50810	0.07580	−0.01056	13.25753	13.25753	0.01417
FTEC_XLK	−1.03590	−0.16821	−0.01719	1.99041	7.94247	−0.04951
VO_IJH	1.45172	0.04047	−0.11282	0.85358	6.50411	0.05829
MTUM_QUAL	−2.51608	−0.45404	−0.02516	7.51781	7.51781	0.03771
XRT_IYC	−7.25084	−0.35705	−0.07738	13.81370	13.81370	−0.00476
VEU_IEFA	−2.45992	−0.30261	−0.03290	0.72000	3.56712	0.00946
EMB_PCY	5.58746	0.25082	−0.03292	0.97218	8.27671	0.02334

Detailed Performance Metrics of Various ETF Pairs, Including Total Profit, Sharpe Ratio, Maximum Drawdown, Recovery Times (Measured in Years), and Correlation with SPY, Spanning the Period from 2000 to 2024.

both approaches. However, the strategy's overall profitability remains constrained, largely due to the short trading windows associated with these pairs. The brief periods during which the pairs maintain cointegration make it difficult to sustain long-term profitability, despite the increased number of trades.

Construction of portfolio: dynamic monthly pair selection with volatility-regime filter

Based on the analysis of the results, we refined the trading strategy and constructed the corresponding portfolio (see Tables 7, 8, 9).

We made significant modifications to the process of strategy implementation and portfolio assembly. First, we

expanded the ETF universe to include 20 US equity ETFs and automated pair selection, eliminating the need for manual matching. At the beginning of each month, we conducted a comprehensive screening process. This involved testing all 190 possible ETF pairs for cointegration using the most recent 200 trading days. Pairs with an Augmented Dickey-Fuller (ADF) p value below 0.05 were retained. From this filtered list, the five pairs with the lowest p values were selected (or fewer if the filter yielded less than five viable pairs). For each chosen pair, we calculated the historical mean (μ) and standard deviation (σ) of the price ratio over the same 200-day lookback window.

Trade entries were monitored daily throughout the following month. A trade was initiated when the absolute value of a pair's z -score exceeded 1.65. This relatively



Table 6 Detailed performance with lower Z-score at 1.5 (equal capital allocation)

Ticker	Total Profit in %	Sharpe Ratio	Maximum Drawdown	Average Drawdown Recovery Time	Max Drawdown Recovery Time	Correlation with SPY
SPY_IVV	35.5920	1.7630	−0.0131	0.0366	0.7096	0.0404
XLE_VDE	−0.2057	−0.0301	−0.0112	5.7489	12.0110	0.0077
XLK_VGT	3.7379	0.3352	−0.0132	1.8269	10.7014	−0.0122
XLV_VFH	3.7964	0.3539	−0.0197	1.6857	11.6219	−0.0020
SLV_GLD	−4.2055	−0.2087	−0.0445	16.3836	16.3836	0.0196
TLT_IEF	0.4893	0.1486	−0.0033	1.7644	5.2658	−0.0113
XLB_VAW	−1.0326	−0.1630	−0.0125	16.9233	16.9233	−0.0143
XLU_VPU	10.7722	0.6540	−0.0113	0.5971	7.7534	−0.0030
QQQ_XLK	−4.2338	−0.2824	−0.0426	21.8274	21.8274	−0.0200
IYR_VNQ	5.5069	0.3923	−0.0124	1.0002	5.7753	0.0480
XLV_VHT	−1.4710	−0.4299	−0.0170	16.4411	16.4411	−0.0136
XLY_VCR	−1.6213	−0.3265	−0.0211	12.2767	12.2767	−0.0160
XLP_VDC	−3.4104	−0.5374	−0.0342	15.1425	15.1425	0.1066
IWM_VTWO	6.4588	1.0153	−0.0040	0.1937	1.1945	0.0259
EFA_VEA	4.0142	0.4303	−0.0072	0.6308	3.4712	0.0021
LQD_VCIT	−1.1434	−0.2023	−0.0171	12.2740	12.2740	−0.0003
HYG_JNK	0.7246	0.1520	−0.0093	2.4651	7.8466	0.0017
IEMG_VWO	−1.7201	−0.2262	−0.0214	8.2740	8.2740	0.0088
IEF_SHY	−2.9137	−0.2752	−0.0326	15.1151	15.1151	0.1180
BND_AGG	2.2681	0.2734	−0.0083	0.6788	3.2685	0.1021
VTI_SCHB	9.5600	1.1197	−0.0048	0.0900	1.0164	0.0000
IWB_VV	1.0035	0.0795	−0.0246	4.5678	14.2274	0.0061
XME_PICK	−11.9937	−0.3367	−0.1210	10.0329	10.0329	0.0061
XBI_IBB	1.1337	0.1654	−0.0088	2.6192	5.2329	0.0142
FTEC_XLK	−1.5159	−0.5227	−0.0155	7.9836	7.9836	0.0184
VO_IJH	−1.5148	−0.1691	−0.0249	18.3233	18.3233	0.0181
MTUM_QUAL	−2.3137	−0.3628	−0.0231	7.5178	7.5178	0.0249
XRT_IYC	−6.3984	−0.3360	−0.0671	13.8137	13.8137	−0.0075
VEU_IEFA	−1.8476	−0.2857	−0.0275	0.8925	3.5315	0.0069
EMB_PCY	−0.5012	−0.0557	−0.0289	2.0525	11.5671	0.0055

Detailed Performance Metrics of Various ETF Pairs, Including Total Profit, Sharpe Ratio, Maximum Drawdown, Recovery Times (Measured in Years), and Correlation with SPY, Spanning the Period from 2000 to 2024.

moderate threshold allowed for an increased number of trading opportunities without sacrificing signal reliability. Each trade involved taking one share of each ETF in the pair. This equal share sizing approach helped maintain simplicity, avoided implicit dollar-neutral hedging, and performed well in back tests. In fact, equal share sizing typically resulted in a negatively skewed distribution of returns—indicating more frequent winners—while equal capital sizing tended to show positive skew but reduced average returns. This relationship remained consistent across z -score triggers of 2.0, 1.8, and 1.6.

Trades were closed when the z -score reverted to below $|0.75|$. This exit threshold was chosen to capture mean-reverting behavior while minimizing overtrading. Execution was inherently dynamic; while we allowed for up to

five pair trades per month, some months yielded fewer qualifying pairs. As a result, the actual amount of deployed capital varied naturally with market conditions.

To enhance robustness under different market regimes, we introduced a volatility-regime overlay. Traditional pair trading relies on mean reversion, which may break down during volatility spikes or crash periods when price dispersion persists. To address this, we adapted the strategy to switch to momentum under extreme conditions. Specifically, we computed a 5-day simple moving average (SMA) of the VIX Index and its expanding-window z -score. When this z -score exceeded 2, indicating abnormally high volatility, the strategy reversed direction and traded in the direction of the price move instead of against it.



Table 7 ETF universe for dynamic volatility-regime portfolio

Ticker	Sector/Description
QQQ	Nasdaq-100 (Large-Cap Tech)
SPY	S&P 500 (U.S. Large-Cap Blend)
IWM	Russell 2000 (U.S. Small-Cap)
VOO	S&P 500 (U.S. Large-Cap Blend)
VB	U.S. Small-Cap
VBK	U.S. Small-Cap Growth
XLF	Financials
KRE	Regional Banks
XLK	Technology
IJR	S&P Small-Cap 600
IVV	S&P 500 (U.S. Large-Cap Blend)
EEM	Emerging Markets
SSO	S&P 500 2x Leveraged
UWM	Russell 2000 2x Leveraged
TNA	Russell 2000 3x Leveraged
SPXL	S&P 500 3x Leveraged
MDY	S&P Mid-Cap 400
XLI	Industrials
IWN	Russell 2000 Value
TQQQ	Nasdaq-100 3x Leveraged

The table lists the 20 ETFs screened each month, covering large-cap, mid-cap, small-cap, sector-specific, emerging-market, and leveraged equity exposures.

Table 8 Performance statistics versus capital-scaled benchmark

Metric	Dynamic Pairs	Scaled S&P 500
Total return	344	405
Annualized return	27.6	32.5
Volatility (σ)	34.0	42.2
Sharpe ratio	0.81	0.77
Sortino ratio	0.055	0.059
Maximum drawdown	−46.8	−98.4
Alpha (annualized)	12.8 ($p = 0.0007$)	—
Beta	−0.14 ($p < 0.0001$)	1.00
Mean Return <i>T</i> -test	2.87 ($p = 0.0041$)	—
Correlation	−0.18	1.00
In-position time	55.4%	100%

Table 9 Illustrative 50–50 blend, monthly re-balanced

Allocation	Blend Sharpe
100% Scaled S&P 500	0.77
50% Scaled S&P 500/50% Pairs	1.22

Benchmarking was crucial given that the pairs portfolio was not continuously invested and capital usage fluctuated. To make an appropriate comparison, we tracked the daily

capital employed by summing the notional cost of all open one-share positions. We then calculated the average capital used over the entire back test period. Using this average value, we constructed a capital-scaled benchmark by applying SPY's daily percentage return to it. The result was a fair, like-for-like benchmark that matched the strategy's variable capital intensity rather than assuming constant full equity exposure.

From a stand-alone perspective, the pairs strategy offered a compelling return-risk profile. While it produced a lower compound annual growth rate (CAGR), it had significantly lower volatility and drawdowns, yielding a Sharpe ratio of 0.81. Its market neutrality was evident, with a beta of −0.14 and a correlation of −0.18 to the broader equity market. The strategy's alpha of 12.8% was statistically significant, underscoring its value as an independent return stream. Notably, the VIX-based volatility overlay proved instrumental during stress periods—such as in 2015, 2018, 2020, and 2022—where it successfully transitioned to a momentum mode, converting drawdown scenarios into profit.

Recognizing the negative correlation between the dynamic volatility-regime portfolio and the SPY Index, we explored a combined allocation. A simple 50/50 mix of the two strategies delivered a notable uplift in performance, raising the Sharpe ratio to 1.22—an improvement of 60%—without employing leverage. This combined portfolio not only generated gains during equity sell-offs but also reduced peak drawdowns and accelerated recovery. Capital efficiency was another strength; with average exposure around 55%, the strategy preserved liquidity and freed up cash for other uses.

In summary, the key takeaways are clear. The strategy's negative correlation is its primary advantage, offering diversification benefits that conventional long-only strategies cannot provide. It functions as a hedge that not only protects but also contributes positively in both tranquil and turbulent markets. In practical terms, even a modest 20–30% allocation to this strategy can substantially smooth portfolio returns and enable risk budget reallocation to higher-return or less liquid investments. In essence, the dynamic, volatility-aware pairs engine is more than a niche alpha source—it is a return-generating hedge that boosts Sharpe ratios, halves worst-case drawdowns, and shines brightest when equity markets are under the most pressure.

Concluding remarks

The findings of this study align with the broader literature, particularly the work of Gatev et al. (1999) and Rad et al. (2016), which highlight both the potential and limitations of pairs trading strategies. These strategies, while capable of being effective under certain conditions, increasingly depend on the stability of cointegration relationships and



the ability to manage associated risks. The mixed results observed, particularly regarding profitability and drawdown recovery, underscore the challenges noted in the literature, and emphasize the need for continued refinement of pairs trading methodologies.

The study confirms that the effectiveness of pairs trading is heavily contingent upon the stability and persistence of cointegration relationships between asset pairs. Notably, lowering the z -score threshold from 2 to 1.5 revealed more trading opportunities and improved total profits, but the strategies still faced significant challenges due to short trading windows and increased volatility. These findings are consistent with prior research, such as Do and Faff (2010) and Rad et al. (2016), which suggest that the profitability of pairs trading has diminished over time due to increased market complexities and risks.

Balancing trading sensitivity with risk management is crucial. While more sensitive thresholds can uncover additional opportunities, they also increase exposure to market noise and the risk of deeper drawdowns. This trade-off aligns with the observations of Vidyamurthy (2004) and Do and Faff (2012), who highlighted the need for adaptive strategies capable of responding to dynamic market conditions.

The effectiveness of ETF pairs trading strategies is highly sensitive to prevailing market conditions, which can significantly impact profitability and risk. Periods of heightened volatility, such as during financial crises or geopolitical uncertainty, can disrupt mean-reverting relationships, causing pairs to diverge for extended periods instead of reverting. Similarly, liquidity constraints—especially in less actively traded ETFs—can increase transaction costs and slippage, reducing net returns. Structural market changes, including regulatory shifts, algorithmic trading proliferation, and changes in market microstructure, can also alter historical relationships between assets, diminishing the reliability of past correlations and cointegration measures. Macroeconomic factors, such as shifts in interest rates, inflation expectations, or sectoral rotation, can further influence price movements, affecting the profitability of pairs trading. By explicitly considering these market dynamics, traders can refine their strategies to account for regime changes and reduce exposure to adverse conditions.

Potential improvements to the pairs trading strategy include the development of adaptive thresholds that adjust based on market volatility or other indicators, enhancing the strategy's robustness in different market environments. Integrating fundamental analysis with cointegration testing could help identify more stable and profitable pairs,

improving the strategy's long-term viability. Additionally, incorporating more sophisticated risk management techniques, such as dynamic position sizing or stop-loss mechanisms, could mitigate the impact of adverse market movements and reduce drawdown recovery times.

The analysis across different z -score thresholds provided valuable insights into the dynamics of pairs trading strategies. Lowering the z -score threshold resulted in a noticeable increase in trading opportunities and profitability; however, this was accompanied by heightened risk, particularly in terms of maximum drawdown. This highlights the critical challenge of balancing more frequent trading opportunities with managing associated risks.

A key observation is the short trading windows during which ETF pairs maintain their cointegration relationships, limiting the ability to capitalize on the strategy over the long term. Even with increased trading frequency, the transient nature of these relationships makes it difficult to sustain consistent profitability, particularly in markets where fundamental or macroeconomic factors driving underlying assets diverge. The study also underscores the importance of diversification within the pairs trading strategy. The performance of individual ETF pairs varied significantly, necessitating a diversified portfolio of pairs to mitigate the impact of any single pair's underperformance on the overall portfolio.

In conclusion, while pairs trading remains a viable strategy for exploiting market inefficiencies, its effectiveness is increasingly challenged by the need to manage the instability of cointegration relationships and associated risks. The findings emphasize the need for continuous refinement of the strategy, including adaptive thresholds, improved pairs selection, and robust risk management practices. By addressing these challenges, it is possible to enhance the effectiveness of pairs trading, ensuring its continued relevance in evolving financial markets. Finally, while the results are robust within the studied period, they are inherently sample-dependent which means that findings may differ under different market regimes or in future periods.

Appendix

See Figs. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 and 11.

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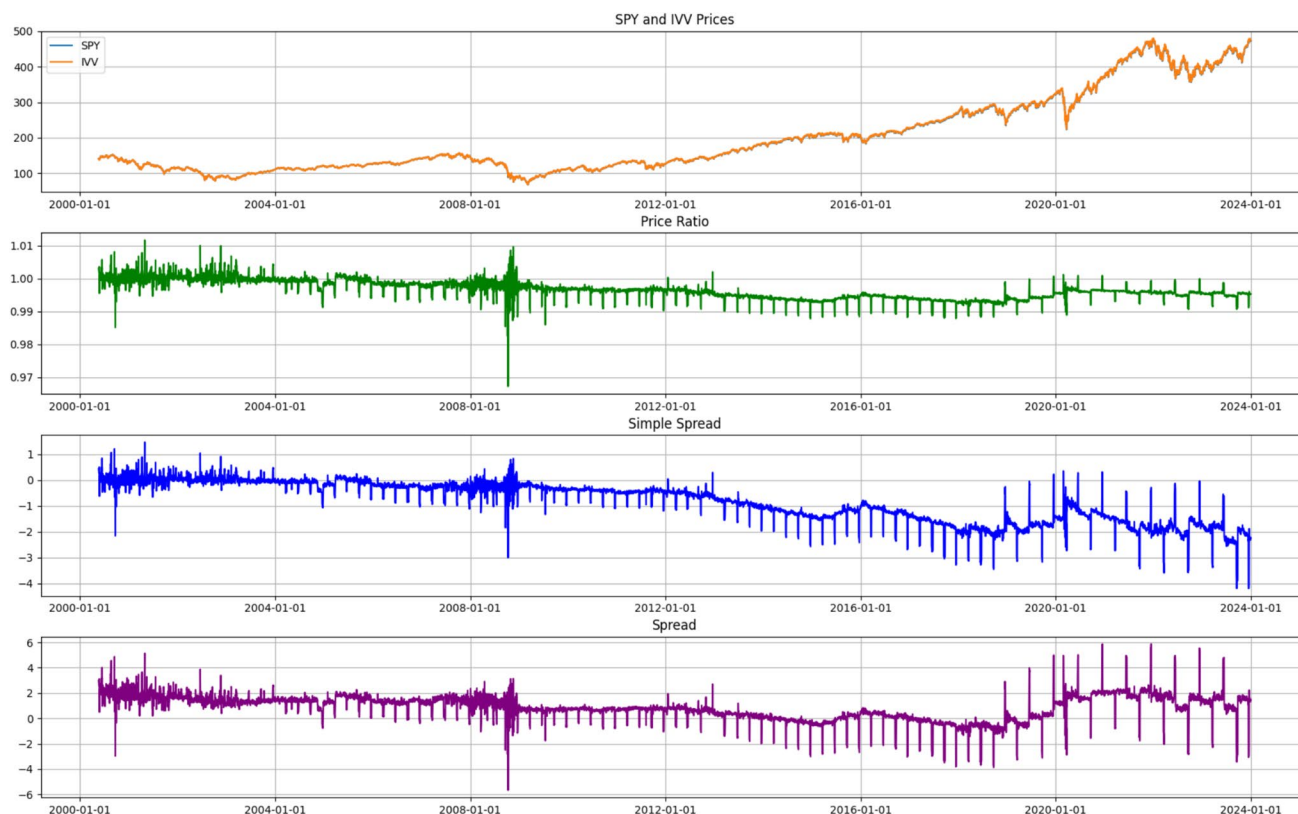


Fig. 1 Price and spread analysis of SPY and IVV (2000-01-02 to 2024-01-02). *Notes:* Top Subplot: Price Trends of SPY (SPDR S&P 500 ETF) and IVV (iShares Core S&P 500 ETF) over the period from January 2, 2000, to January 2, 2024; Second Subplot: Price Ratio (SPY/IVV), illustrating the relative price movements between SPY and IVV; Third Subplot: Simple Spread (SPY-IVV), showing

the direct difference in prices between SPY and IVV; Bottom Subplot: Spread derived from the Engle-Granger 2-Step method, indicating the cointegrated relationship between SPY and IVV. It should be acknowledged that the algorithm used in the study detects a non-tradeable mean reversion opportunity for the pair SPY-IVV.

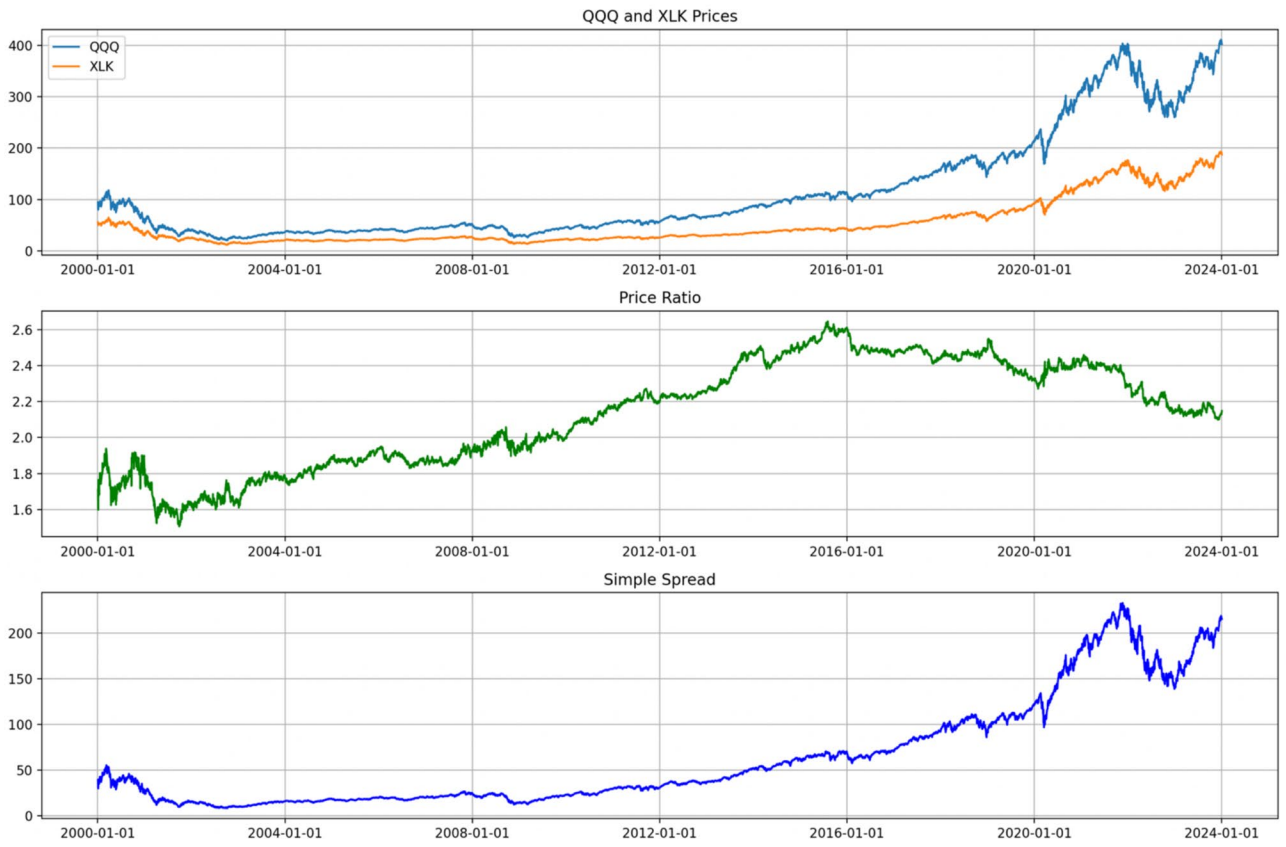


Fig. 2 Price and spread analysis of QQQ and XLK (2000-01-02 to 2024-01-02). *Notes:* Top Subplot: Price Trends of QQQ (Invesco QQQ Trust) and XLK (Technology Select Sector SPDR Fund) over the period from January 2, 2000, to January 2, 2024; Second Subplot:

Price Ratio (QQQ/XLK), illustrating the relative price movements between QQQ and XLK; Third Subplot: Simple Spread (QQQ–XLK), showing the direct difference in prices between QQQ and XLK.

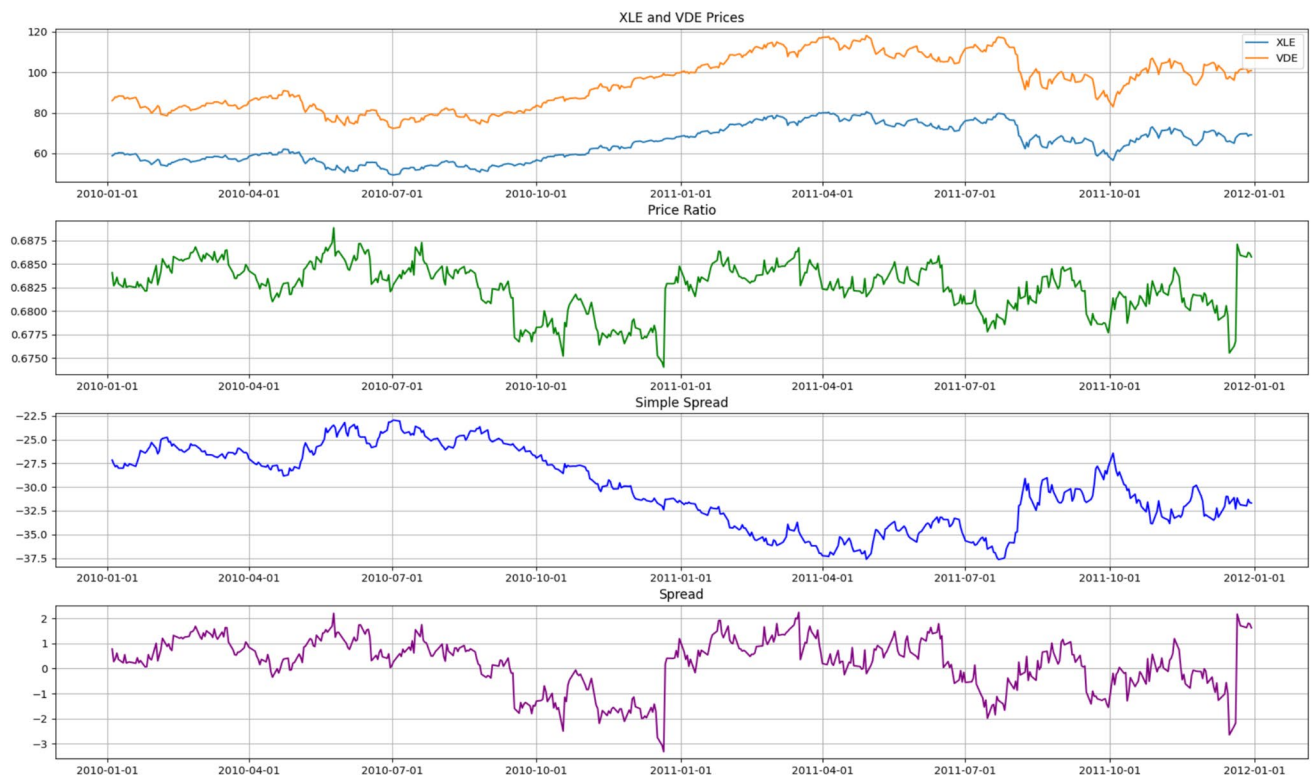


Fig. 3 Price trends and spreads for XLE and VDE (2010-01-03 to 2012-01-03). *Notes:* Top Subplot: Price trends of XLE (Energy Select Sector SPDR Fund) and VDE (Vanguard Energy ETF) over the period from January 3, 2010, to January 3, 2012; Second Subplot: Price Ratio (XLE/VDE), illustrating the relative price movements

between XLE and VDE; Third Subplot: Simple Spread (XLE–VDE), showing the direct difference in prices between XLE and VDE; Bottom Subplot: Spread derived from the Engle-Granger 2-Step method, indicating the cointegrated relationship between XLE and VDE.

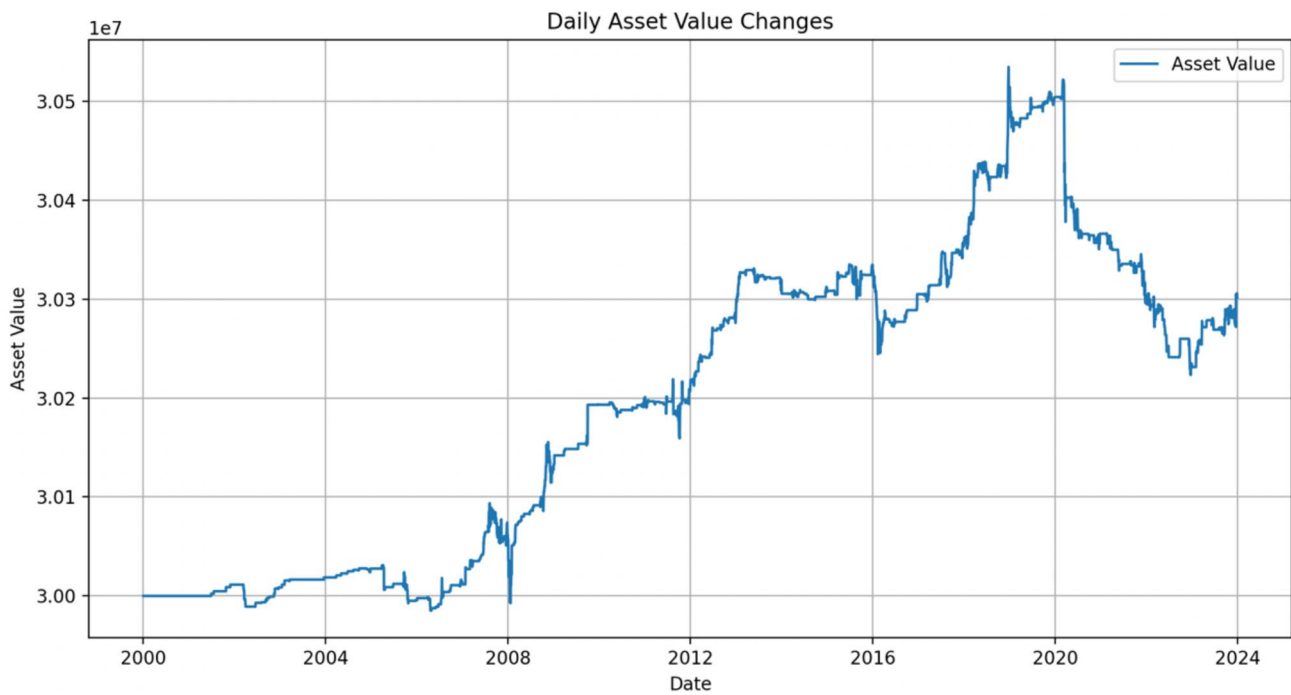


Fig. 4 Portfolio performance 2000–2024 (Method 1: Equal Number of Share). *Notes:* Performance of a 30 ETF Pair Portfolio from 2000 to 2024 Using a Z-Score Threshold of 2, with Equally numbered long and short positions and no transaction costs.

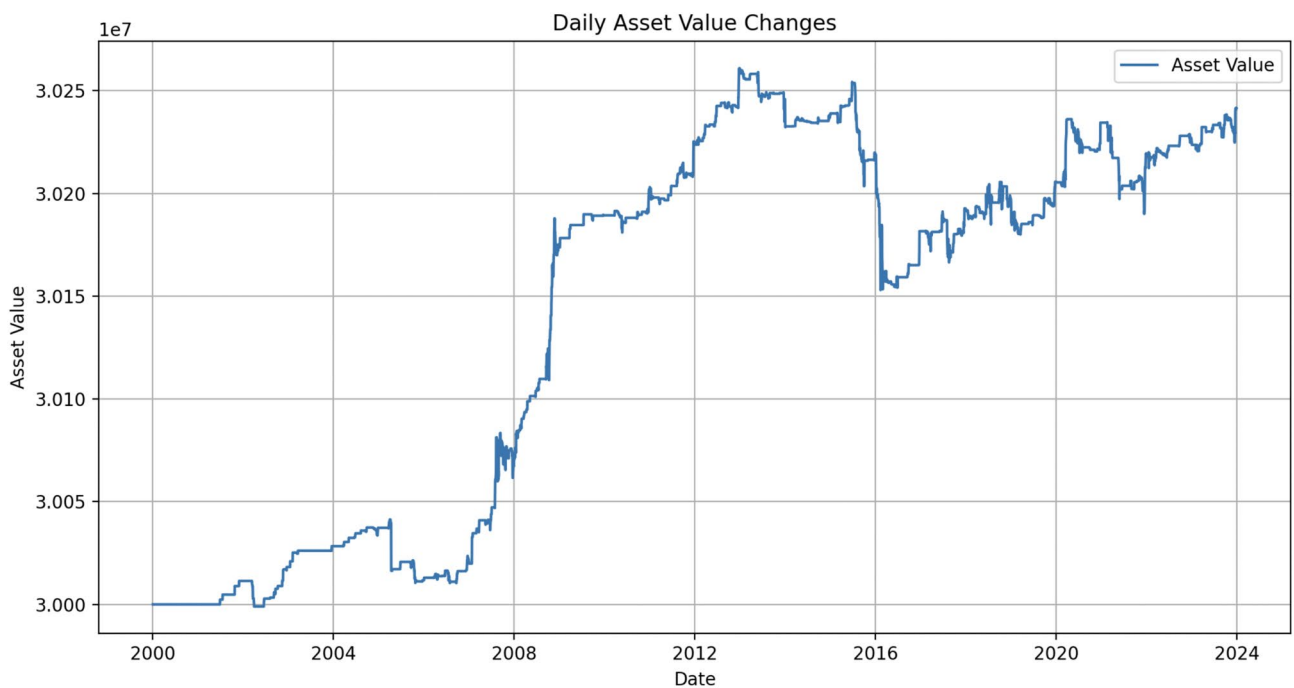


Fig. 5 Portfolio performance 2000–2024 (Method 2: Equal Capital Allocation). *Notes:* Performance of a 30 ETF Pair Portfolio from 2000 to 2024 Using a Z-Score Threshold of 2 with Equal Value Positions of \$500,000 in Both Long and Short Trades.

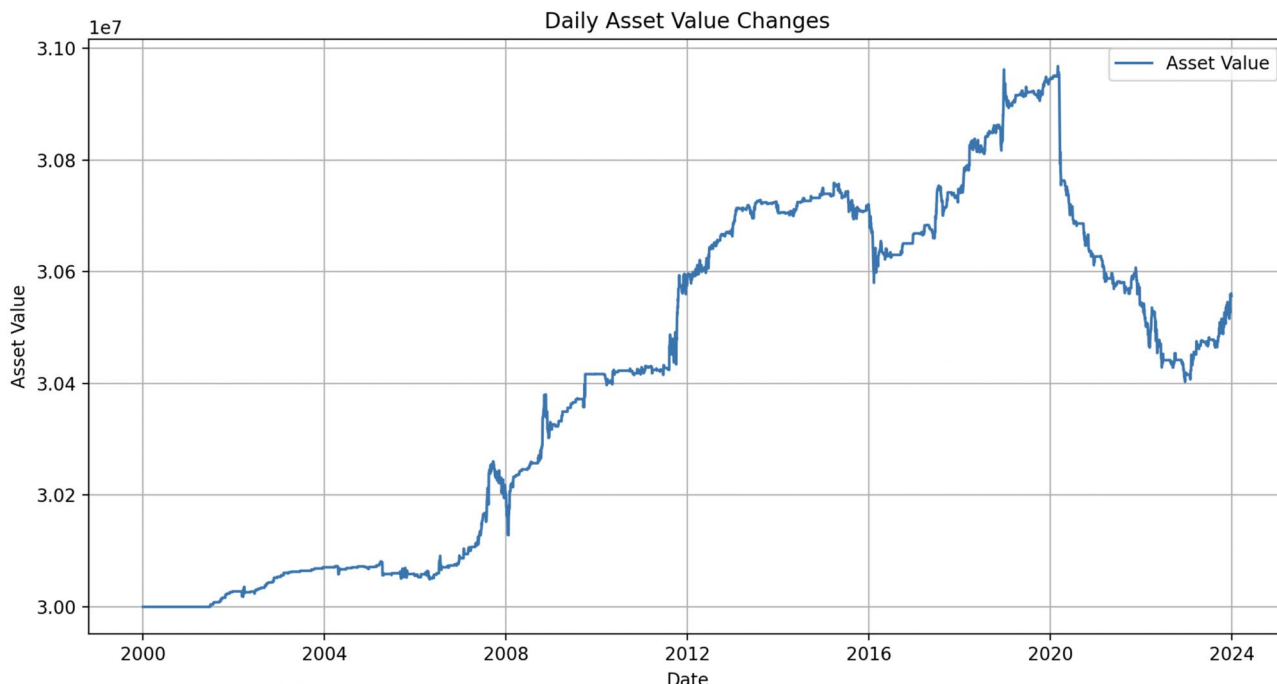


Fig. 6 Portfolio performance 2000–2024 with Z-score at 1.5 (Method 1: Equal Number of Share). *Notes:* Performance of a 30 ETF Pair Portfolio from 2000 to 2024 Using a Z-Score Threshold of 1.5, with Equally Numbered Long and Short Positions and No Transaction Costs.

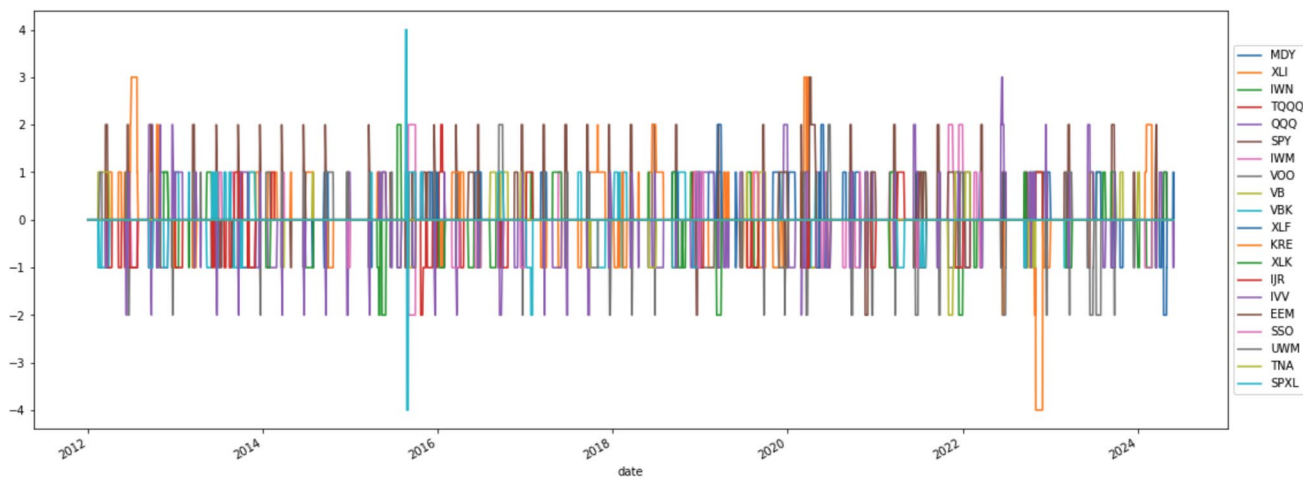


Fig. 7 Dynamic volatility-regime portfolio position 2012–2024.06. *Note:* The y-axis represents the number of shares held in each position.

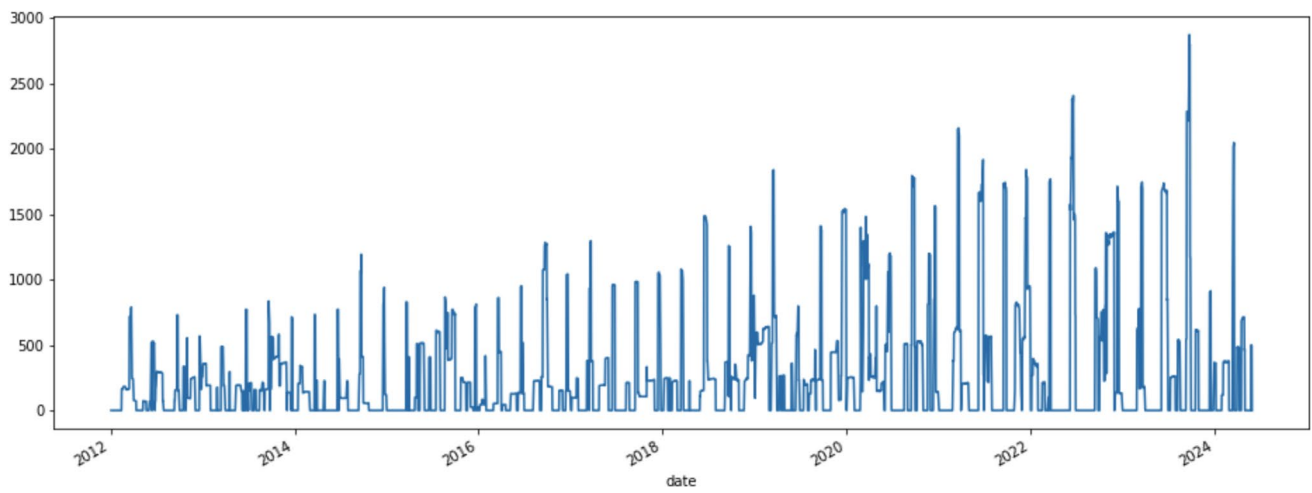


Fig. 8 Dynamic volatility-regime portfolio capital employed 2012–2024. *Notes:* The y-axis represents the dollar value of the position.

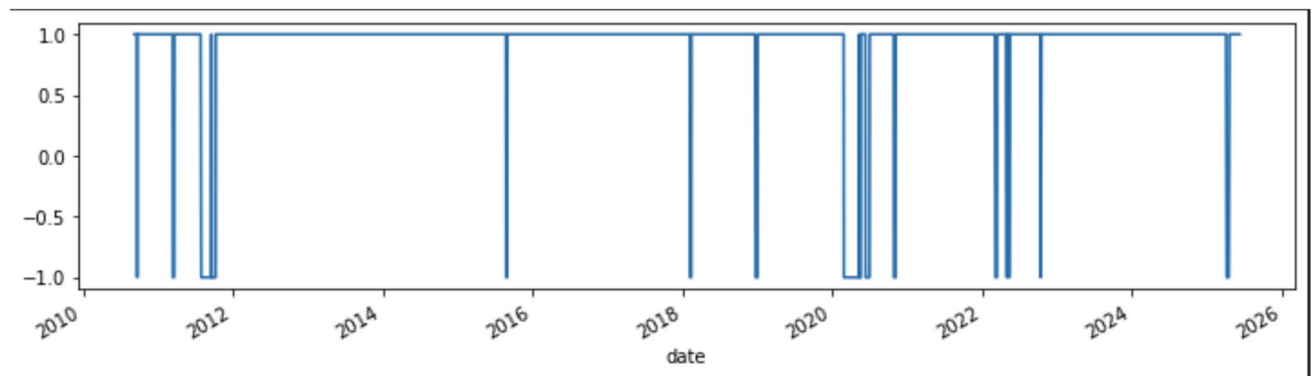


Fig. 9 VIX Index Reime 2012–2026. *Notes:* The y-axis shows whether the expanding historical z -score is above 2: 1 denotes “yes,” and -1 denotes “no.”

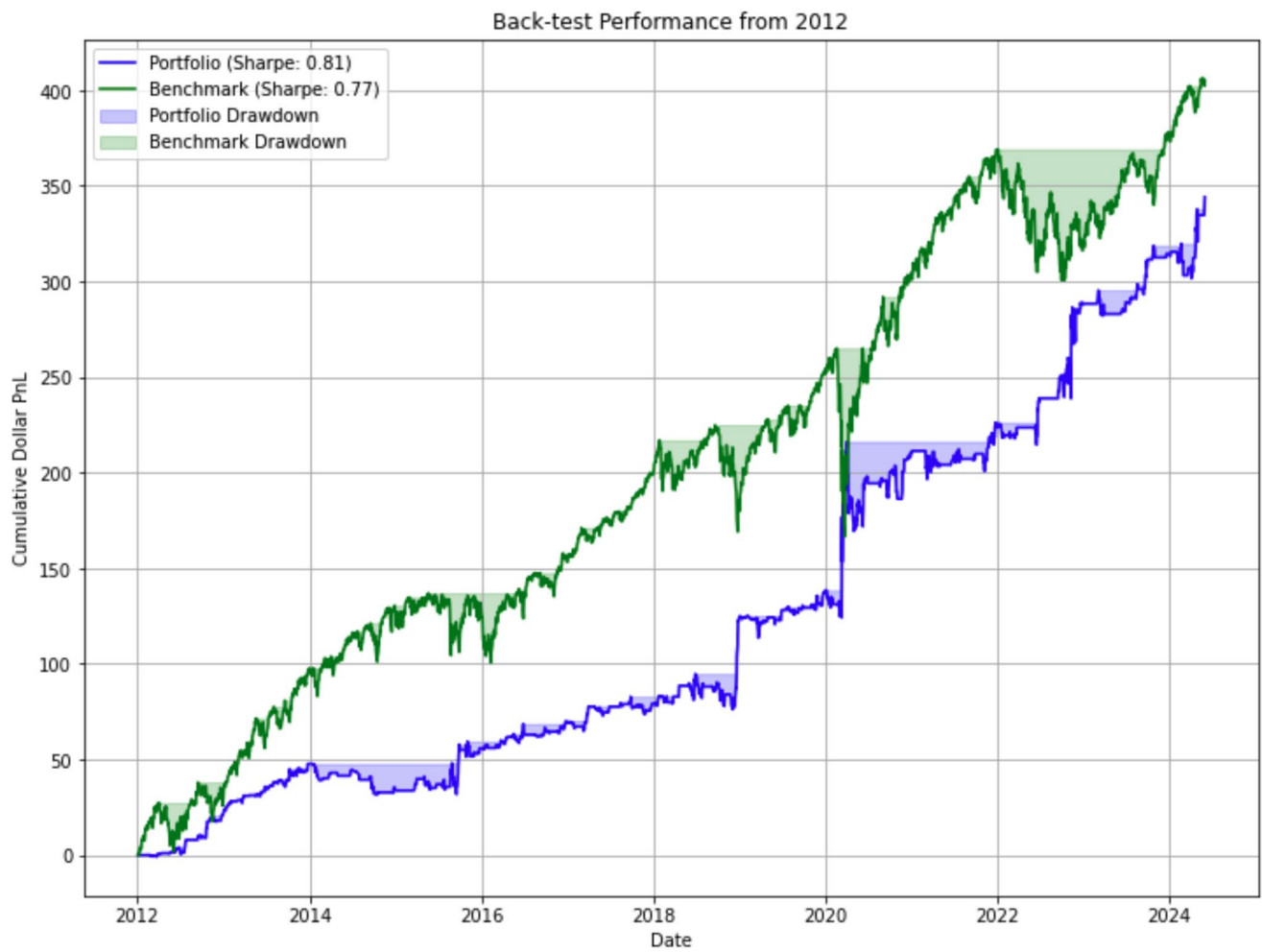


Fig. 10 Dynamic volatility-regime portfolio performance 2012–2024.06

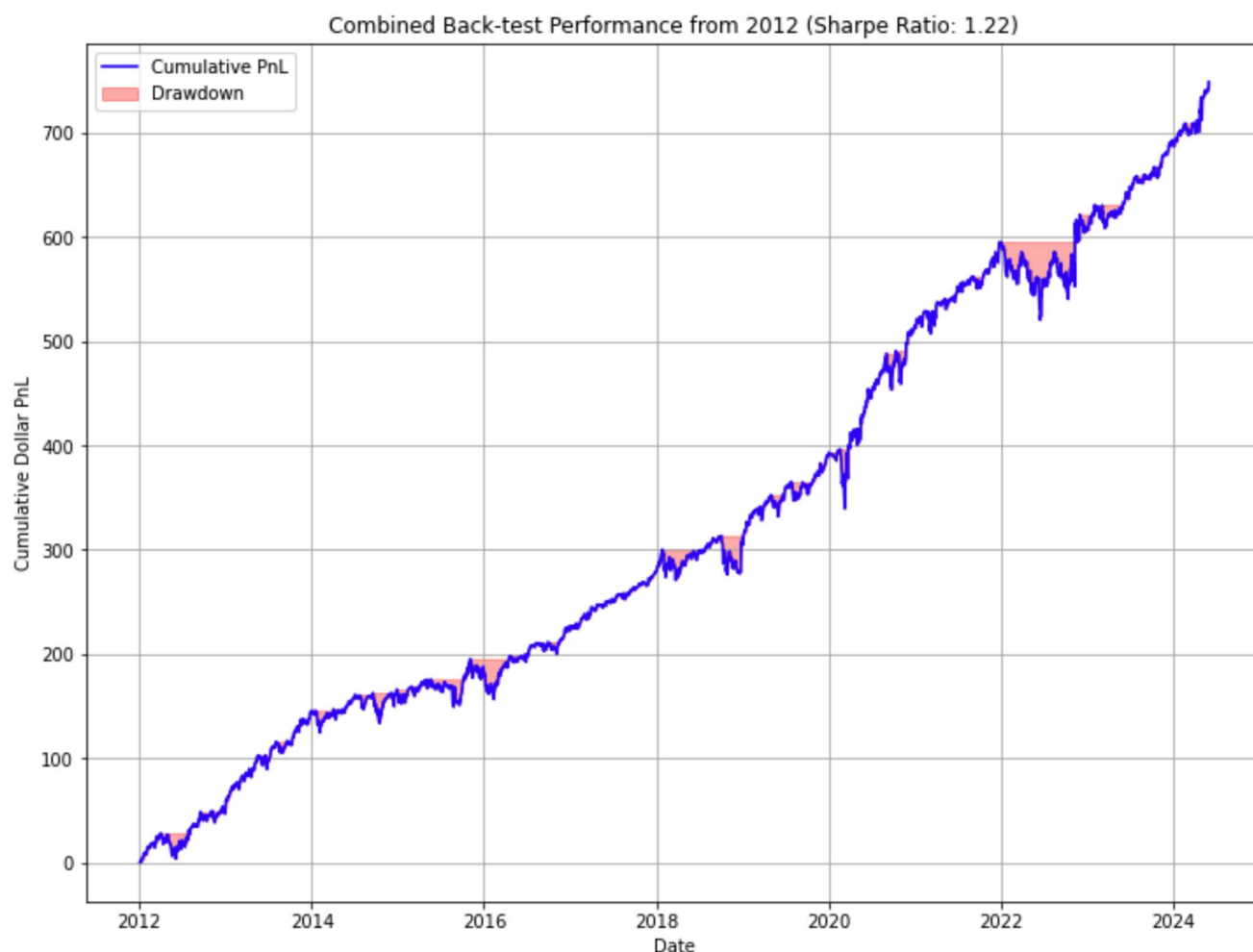


Fig. 11 Combine dynamic volatility-regime portfolio and buy and hold strategy performance 2012–2024.06

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Kezhong Chen is a Quantitative Alpha Researcher at a global financial institution, where he develops and applies advanced statistical and machine learning models to identify market inefficiencies and support systematic investing. He holds an M.Sc. in Finance from Cranfield University and a BSc in Mathematics from Imperial College London. A CFA charterholder, his research interests include alternative data integration, factor-based strategies, risk modeling, and the application of cutting-edge quantitative techniques to portfolio construction.

Dr. Constantinos Alexiou is a Professor of Macroeconomics and Policy at Cranfield School of Management where he delivers Economics and Business related courses across the full range of the School's post-graduate and post-experience executive management programmes. The focus of his research revolves inter alia around Applied Macroeconomics, Macroeconomic Policy, International Finance, Patent Systems, Heterodox Economics etc.. He has authored over 100 publications in academic journals such as the *Journal of Post Keynesian Economics*, *Contributions to Political Economy*, *Structural Change and Economic Dynamics*, *International Journal of Finance and Economics*, *Journal of World Business*, *International Business Review*, etc. He is the founding editor of the *International Journal of Economics*, and a member of the European economic forum for alternative economic policy in EU. He is a frequent contributor to many international conferences.





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Cointegration-based pairs trading: identifying and exploiting similar exchange-traded funds

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