Tetravariate Statistical Arbitrage in North American Logistics and Transport

TetraPort Capital

Abstract

We propose an investment strategy based upon statistical arbitrage and apply a novel machine learning methodology to search for mean reverting patterns in North American logistics and transport equity markets by identifying unrestricted cointegrating parameters yielding a market neutral return. The strategy generated a 36.02% *CAGR in an out-of-sample backtest between* 2017 *and* 2024*, with an annualised Sharpe ratio of* 0.79.

1 Economic Hypothesis

Statistical arbitrage emerged in the 1980s, building upon pairs trading techniques pioneered by Morgan Stanley's quantitative team. Our strategy exploits mean reverting price relationships, identifying temporary deviations from equilibrium to construct long/short portfolios. Unlike traditional arbitrage, which targets absolute mispricings, statistical arbitrage focuses on relative mispricing between cointegrated assets. Our strategy rejects Fama's strong form of the Efficient Market Hypothesis (EMH) [1], but aligns with its weak and semi-strong forms, suggesting that while markets are generally efficient, short-term pricing inefficiencies can arise due to market frictions. Additionally, Arbitrage Pricing Theory (APT) [2] supports the idea that deviations from fair value, absent fundamental justification, tend to revert over time.

Our investable universe consists of 30 U.S.-listed equities spanning railroads, trucking, air freight, shipping, warehousing, and logistics services, representing the core infrastructure of the North American supply chain. These companies exhibit deep economic interdependencies, forming the backbone of domestic and global trade. Their structural reliance on shared economic drivers, such as fuel costs, trade volumes, and industrial production, ensures a fundamental linkage that supports our trading strategy.

All selected equities are dollar-denominated assets listed on U.S. exchanges, eliminating both foreign exchange (FX) and market mismatch related risks. The companies range from large-cap industry leaders like Union Pacific (UNP) and FedEx (FDX) to specialized mid-cap logistics providers such as Kirby (KEX), offering a diverse yet fundamentally interconnected market landscape.

The transportation and logistics industry exhibits a long-run equilibrium in price relationships due to high interdependence across subsectors. Freight movements are not isolated events but rather a continuous process linking multiple transportation modes. For example, rail operators rely on trucking firms for first-and-last-mile delivery, while warehousing and distribution centres coordinate shipments across rail, air, and sea. This interconnectedness ensures that price movements among these firms remain systematically linked over time.

A key justification for long-run equilibrium within the sector lies in macroeconomic fundamentals. The sector's performance is tied to broad economic indicators, including industrial production [3], trade policy [4], and fuel price dynamics [5]. Additionally, the industry is highly structured, with long-term contracts and pricing mechanisms that reinforce stability. Many logistics firms operate under long-term contractual obligations with customers, ensuring stable revenue streams and reducing uncertainty and creating predictable price relationships. This characteristic ensures that cointegration-based strategies remain viable over time, as the economic forces linking firms persist despite temporary market shocks.

The sector is also highly sensitive to macroeconomic conditions, creating temporary mispricings that our strategy is designed to exploit. For instance, fuel price surges affect all transportation firms simultaneously, creating temporary divergence in stock prices before costs are passed through and equilibrium is restored. Trade disruptions (e.g., port congestion, supply chain delays) cause temporary inefficiencies but ultimately correct as shipments normalize, and intermodal freight relationships (rail-to-truck-to-air) ensure price adjustments across subsectors, leading to mean reverting behaviour among interconnected firms. Michail and Melas [6] demonstrate that shipping stocks maintain a stable long-term relationship with freight rates, reinforcing the idea that transportation stocks, more broadly, tend to revert to equilibrium following short-term shocks. These structural interdependencies create persistent economic relationships, making the transportation and logistics sector well-suited for our strategy.

Another major advantage in implementing our strategy in the transportation & logistics industry is that large quantitative hedge funds tend to overlook this sector in favour of other highly liquid assets, such as technology or financial stocks. By targeting an under-exploited market with unique inefficiencies, our model captures alpha from mispricings that are ignored by conventional statistical arbitrage strategies, reducing competition and avoiding overcrowded trade setups.

2 Implementation

2.1 Searching for Cointegrated Candidates

We have $27,405$ possible combinations of four, derived from our investable universe of 30 equities where each of these combinations forms what we refer to as a *candidate*. We start by taking the logarithmic price series for each of our four assets $X_1 \dots X_4$ and form a linear combination Y such that:

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \tag{1}$$

where the values $\beta_1 \dots \beta_4 \in \mathbb{R}$ are unrestricted cointegrating parameters and $Y \in I(0)$. In basic cointegration models, such as the Engle and Granger [7] test, an ordinary least squares (OLS) regression estimates the following model:

$$X_1 - \beta_2 X_2 - \beta_3 X_3 - \beta_4 X_4 = \alpha + \epsilon \tag{2}$$

which is a stationary process as α is the constant of the regression and $\epsilon \sim w.n.(0, \sigma^2)$, given that there is no serial correlation. The weakness of this is that $\beta_1 := 1$ and we would have to evaluate a subset of all possible permutations (of which there are $657,720$) to apply a weight of 1 to each equity. As this is a subset, only the position of the first equity matters, so, for example, combinations $\{A, B, C, D\}$, $\{A, C, D, B\}$ and $\{A, D, C, B\}$ are all functionally equivalent. Instead, we use the Johansen maximum eigenvalue test [8], placing our hypothetical linear combination of four equities into vector error form, such that we can test the rank of the derived cointegration matrix by searching for its maximum eigenvalue. If the resulting value is greater than zero at the 5% significance level, then the hypothetical candidate is deemed to be cointegrated and the parameters $\beta_1 \dots \beta_4$ take the values from the main diagonal of the cointegration matrix. Our strategy tests the series Y for cointegration in a time period T_2, which we define as the 20 most recent trading days. We then assess whether the candidate was also cointegrated during the previous 20 trading days immediately prior to T_2, denoted as T_1. This assessment applies the weightings $\beta_1 \dots \beta_4$ from T_2 and uses the Augmented Dickey-Fuller (ADF) test for stationarity, mitigating the risk of finding spurious cointegrating relationships between our candidates. Using Y from (1) we test:

$$\Delta Y_t = \alpha + \omega t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \epsilon_t \tag{3}$$

under the null hypothesis of $\gamma = 0$ against the alternative of $\gamma < 0$, where ω denotes the time trend coefficient, and $\delta_i, i = 1, \dots, t$ are the auto-regressive coefficients of ΔY. We deem that the candidate was also cointegrated in T_1 when we reject the null hypothesis at the 5% significance level and discard the group when we fail to reject, assuming that the relationship was spuriously formed.

2.2 Determining the Future Feasibility of a Candidate

Once we have deemed that a candidate is cointegrated across $[T_1, T_2]$, we utilise a machine learning algorithm to predict whether it will remain cointegrated through the next 20 days of trading, denoted T_3. Here, we utilise a Random Forest (RF) model, expanding upon previous work by Chaudhuri et al. [9] which predicted price ratios for individual assets in pairs trading. Instead, we analyse how Y evolves throughout our supervised testing period, predicting whether the cointegrating relationship will continue through T_3. By doing this, our model can also be easily extended for any n assets, should we wish to look for more complicated relationships in the future. Following from (1), our model can theoretically solve:

$$Y = \sum_{i=1}^{n} \beta_i X_i \tag{4}$$

for any $n \geq 2, n \in \mathbb{N}$. Unlike traditional RF models that rely on static features, our approach dynamically adapts to new data using an expanding window training framework, trained on lagged values of $Y_i \dots Y_t, i = 1, \dots, t$ as input features, predicting Y_{i+1} at every step. This method allows us to utilise > 30 input features to maintain predictive accuracy over time, whilst also minimising the risk of overfitting which other models such as CNNs and transformers are at high risk of. Our model correctly predicts whether the candidate will remain cointegrated in T_3 with 68% accuracy, making errors in 32% of cases. Of these, 79% are Type-II errors (false-negatives), incorrectly rejecting valid candidates, while 21% are Type-I errors (false-positives), incorrectly accepting invalid ones. The losses from Type-I errors are limited by a hard 15% stop-loss.

Finally, we filter our list of viable candidates by checking the half-life of the cointegrated spread to ensure that mean reversion occurs within a reasonable amount of time. Choosing a time window is an arbitrary choice, which is set to 10 days as we trade a candidate through

T_3 for a maximum of 20 days. We calculate half-life using:

$$\frac{-log(2)}{\gamma} \tag{5}$$

where γ is the value from the ADF test in section 2.1.

2.3 Generating Long/Short Trading Signals

Once Y has been deemed viable, trades are executed using z-scores which is the number of standard deviations an observed value is from the mean and is calculated using:

$$z = \frac{x - E(Y)}{\sigma(Y)} \tag{6}$$

We trade the spread when the z-score breaches the confidence interval $[-1, 1]$ and close our trades when either the z-score reaches/crosses 0, taking profit, or if the candidate reaches our hard stop-loss of 15%. More simply, we long the group with weightings $\beta_1 \dots \beta_4$ when $z \leq -1$ and short the group with weightings $-(\beta_1 \dots \beta_4)$ when $z \geq 1$.

With regards to portfolio construction, capital is equally assigned to each candidate and no leverage is implied within the strategy, such that only the capital available is risked with each trade. This means that we can immediately cover a margin call, should one occur, by using the cash originally generated from our short positions. Although this is a limitation of our strategy's implementation, we do have the ability to deploy some or all of this capital to leverage its returns. Capital deployed to a candidate is also limited by the individual stock's 1-year daily average volume such that our market orders are capped at 2% of daily turnover.

3 Risks

3.1 Spurious Relationships and Model Instability

Overfitting or data-mining bias may result in spurious statistical relationships being observed rather than from our assets truly deviating from their mean, which could be detrimental should our forecasting engine report a high number of false-positives across such a large dataset. Our model is able to effectively manage this risk with a low Type-I error rate of 21% (or $\approx 3\%$ of all of our trades) and through the use of a hard stop-loss at 15%.

3.2 Macroeconomic and Sector-Specific Risks

The North American logistics and transport sector is highly sensitive to macroeconomic shocks, such as fluctuations in fuel prices and changes in trade policies. For instance, a study by Mansfield Energy [10] shows that an increase in fuel prices from \$2.00 to \$3.00 per gallon can lead to a 50% rise in interest costs, significantly impacting logistics operations. In response to these challenges, our strategy focuses on exploiting relative price movements rather than absolute changes in individual equity prices. This approach allows us to capitalise on the relationships between our assets, which can be particularly valuable in a sector where macroeconomic shocks have a broad impact. However, it's important to recognise that these shocks do not affect all companies uniformly. McKinsey's analysis [11] highlights that economic downturns broadly affect the sector, yet some companies exhibit greater resilience than others, leading to variability in their responses to these shocks. Despite these sector-wide challenges, the cointegration of our candidates remains unaffected by macroeconomic or policy shocks, making our strategy relatively robust to such events. However, market idiosyncrasies, such as M&A activity, can disproportionately affect at least one asset within a candidate and breaching the concept behind APT [2]. By applying a hard stop-loss of 15% to each candidate and only trading over T_3 before re-evaluating whether the candidate is still cointegrated, our strategy effectively mitigates against market idiosyncrasies.

3.3 Exogenous Liquidity Shocks

If rival long/short equity funds operating within the same investable universe as ourselves were to suddenly unwind their positions due to exogenous factors, our hard stop-loss may be triggered for some candidates even if mean reversion would have happened otherwise. As we trade a candidate's spread rather than an individual stock's price, such losses may be higher than 15% as market orders are sent to the exchange attempting to flatten our position in an illiquid environment, forcing us to "walk-the-book" more than anticipated. This was observed in August 2007, where many statistical arbitrage funds were forced to liquidate their positions due to a liquidity shock caused by an increasing amount of leveraged capital being deployed into similar equity spheres [12]. Such shocks should not adversely affect the liquidity of the positions being traded in our strategy, as the logistics and transport sector is very niche and therefore we expect to be less exposed to any illiquidity risks.

4 Analysis of Strategy Prospects

4.1 Liquidity and Capital Considerations

Statistical arbitrage strategies are inherently constrained by liquidity, as excessive capital deployment can erode mispricing opportunities and impact order book dynamics. The liquidity of our investable universe is a critical factor in ensuring scalability without materially influencing price behaviour. Our selection of 30 U.S.-listed equities has an average 3-month intraday trading volume of $\$141,780,052.20$ per equity, ensuring sufficient liquidity. However, this distribution is skewed by large-cap players such as FedEx (FDX) and Union Pacific (UNP), while the least liquid equity in our portfolio – Heartland Express, Inc (HTLD) – averages $\$4.71M$ in daily trading volume.

To preserve execution efficiency, we apply a 2% market impact threshold, meaning our strategy should not exceed 2% of an asset's daily volume in any given trade, ensuring that our orders remain small enough to avoid slippage while still allowing capital scalability. Given that we deploy capital across four-asset groups, with an average of 8-12 active trades at any time, our maximum theoretical capital deployment is approximately $\$50M$ before significant slippage effects emerge. However, real-world conditions suggest that our actual liquidity threshold is closer to $\$35M - \$40M$, particularly when executing market-neutral positions that require simultaneous long/short orders across multiple equities.

Moreover, our backtested execution data shows that bid-ask spreads within the transportation and logistics sector remain relatively stable, even during periods of heightened market volatility. Over a 5-year period, the median bid-ask spread across our portfolio has declined by 14% , reflecting improved market depth and institutional participation. Current macroeconomic conditions—characterized by elevated inflation, interest rate uncertainty, and persistent supply chain disruptions—are likely to sustain this liquidity profile into 2024, ensuring that our strategy can be deployed at scale without material execution risks.

Assuming a maximum deployment of 2% of daily trading volume per stock and given an average daily trading volume of \$14.78M across our 30-stock universe, we estimate that each group of 4 stocks can absorb approximately \$1.18M without significantly impacting market prices. With an average of 43 groups traded simultaneously, our daily capital deployment reaches \$9.46M. Over a 20-day holding period, this allows for a total capital allocation of approximately \$406.74M before liquidity constraints become a concern, hence as long as we stay below this figure, we could scale up our strategy over time. An example of one of our traded candidates is shown in Figure 6.

4.2 Risk-Adjusted Performance and Future Outlook

Across our 7-year out-of-sample backtesting period, the strategy yielded a gross return of 1055.76%, equating to a 36.02% CAGR with a daily volatility of 3.86%, equating to an annualised Sharpe ratio of 0.79. This significantly outperforms both the Vanguard S&P 500 ETF (VOO) and the iShares U.S. Transportation ETF (IYT) which returned 138.03% and 63.89% respectively. Our portfolio's performance against these indices is shown in Figure 2.

Figure 1 represents our backtest between 2$^{\text{nd}}$ August 2017 and 30$^{\text{th}}$ December 2024. A large proportion of our returns come from the second-half of 2022, where rapid interest rate hikes from the Federal Reserve caused great unrest across financial markets, creating more mispriced opportunities within the market. During this period, we our portfolio held a modest Sharpe ratio of 1.67, greatly outperforming other strategies at the time.

Our strategy had strong negative performance throughout 2023 as shown by the drawdown in Figure 3. This was likely as a result of the Fed holding interest rates high, amid a period where other economic agents were able to predict market movements more accurately, hence increasing its efficiency. The resultant of this was that we detected more spurious relationships at this time, likely as a result of our strategy interpreting exogenous factors as potential candidates.

Looking towards the future, we expect that our strategy will continue to outperform the benchmark indices mentioned above as tariffs are inconsistently imposed by the Trump Administration, with countries imposing and cancelling tariffs of their own in retaliation, resulting in increased market volatility. Furthermore, due to The White House and the FOMC having conflicting targets for the Fed Funds Rate (alongside the risks of tariff-related inflationary pressure), we expect our strategy to continue to perform not only throughout the entirety of this Presidential term, but also into the next election cycle as the next administration attempts to resolve any current conflict.

5 Figures

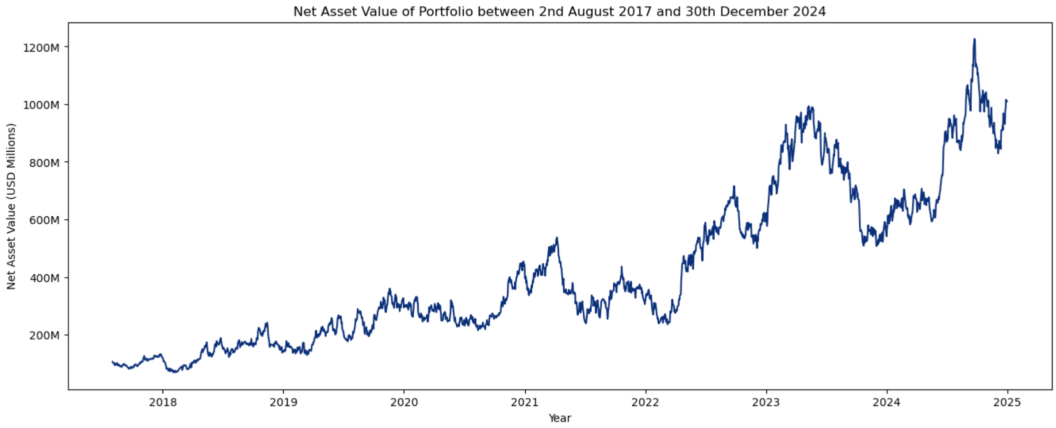

Figure 1: Portfolio Backtest Between 2017 - 2024

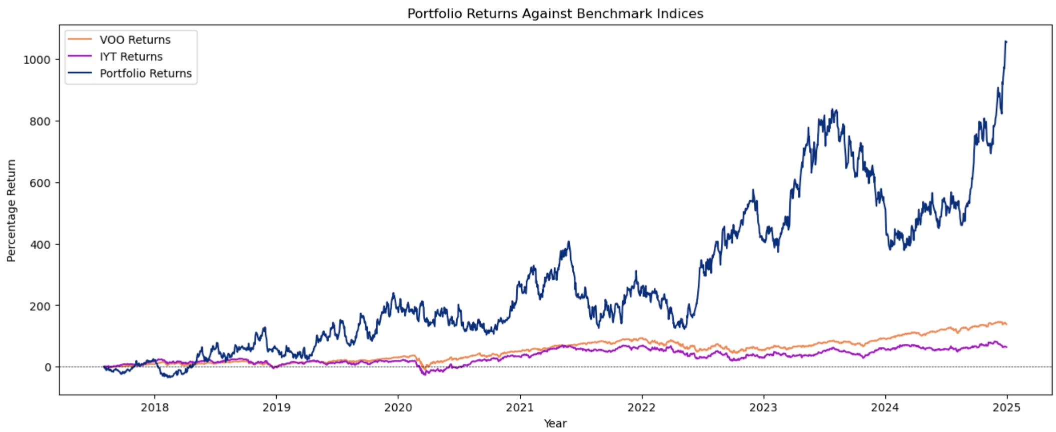

Figure 2: Portfolio Backtest Against Index Benchmarks

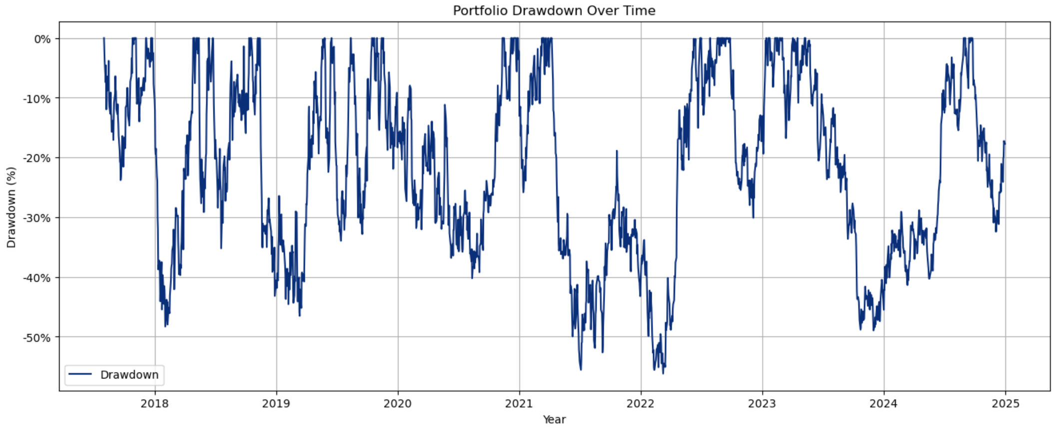

Figure 3: Portfolio Drawdown Throughout Backtesting Period

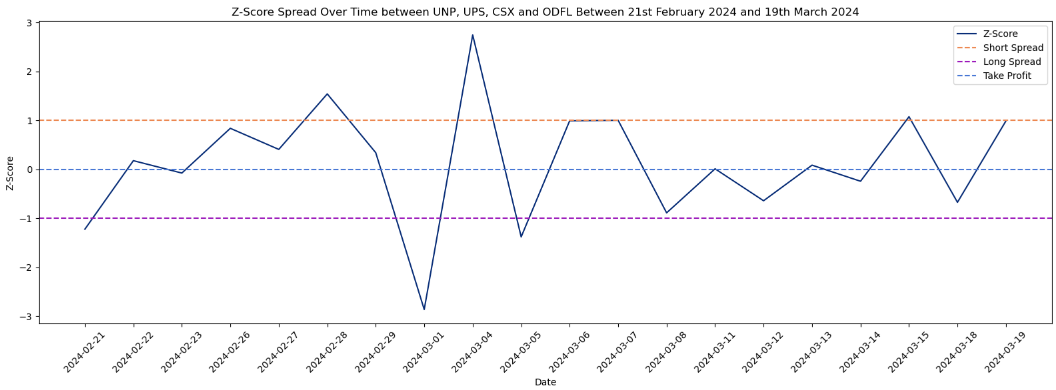

Figure 4: Spread between UNP, UPS, CSX and ODFL

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A Investable Universe

Ticker	Company	Market Cap (USD bn)	Daily Trading Volume (USD mn)
UNP	Union Pacific Corp	150.06	667.98
UPS	United Parcel Service, Inc	98.20	635.19
ODFL	Old Dominion Freight Line, Inc	43.66	296.54
CP	Canadian Pacific Kansas City Limited	72.98	257.25
XPO	XPO Inc	17.08	218.47
WAB	Westinghouse Air Brake Technologies Corp	32.88	202.79
SAIA	Saia Inc	12.72	171.76
JBHT	J.B. Hunt Transport Services, Inc	16.59	137.94
CNI	Canadian National Railway Co	64.81	137.40
EXPD	Expeditors International Of Washington, Inc	15.68	113.15
CHRW	C.H. Robinson Worldwide, Inc	11.61	110.98
KNX	Knight-Swift Transportation Holdings Inc	8.84	104.83
KEX	Kirby Corp	6.11	65.91
GXO	GXO Logistics Inc	4.33	49.27
LSTR	Landstar System, Inc	5.64	45.80
MATX	Matson Inc	4.68	34.64
TFII	TFI International Inc	11.03	27.53
ARCB	ArcBest Corp	2.19	25.02
HUBG	Hub Group, Inc	2.57	23.88
WERN	Werner Enterprises, Inc	2.15	22.59
RXO	RXO Inc	3.26	22.07
SNDR	Schneider National Inc	4.86	21.98
PBI	Pitney Bowes, Inc	1.93	21.66
GBX	Greenbrier Cos., Inc	1.94	20.42
TRN	Trinity Industries, Inc	2.96	16.91
FWRD	Forward Air Corp	0.87	15.92
CJMB	Callan Jmb Inc	0.02	7.94
GNK	Genco Shipping & Trading Limited	0.61	6.37
MRTN	Marten Transport, Ltd	1.22	5.92
HTLD	Heartland Express, Inc	0.89	4.71

Table 1: Market Capitalization and Average 3-Month Daily Trading Volume of Logistics Companies