

MOMENTUM PREMIERANOMALY

A MODULAR APPROACH TO THE MOMENTUM STRATEGY DESIGN

This whitepaper outlines how we built the Stratum Index—a modular, multi-algorithm strategy designed to adapt across market regimes. It covers the principles behind its construction, the constraints we use to manage risk, and how it has performed in historical stress tests.

Disclaimer: For informational purposes only. This is not financial advice or an offer to buy or sell securities. Performance examples are hypothetical.



About Quanta 72

Quanta 72 is a data provider focused on market structure and systematic asset rotation. We produce a multi-algorithm model that tracks momentum and stress across global asset classes.

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Summary: Stratum Index

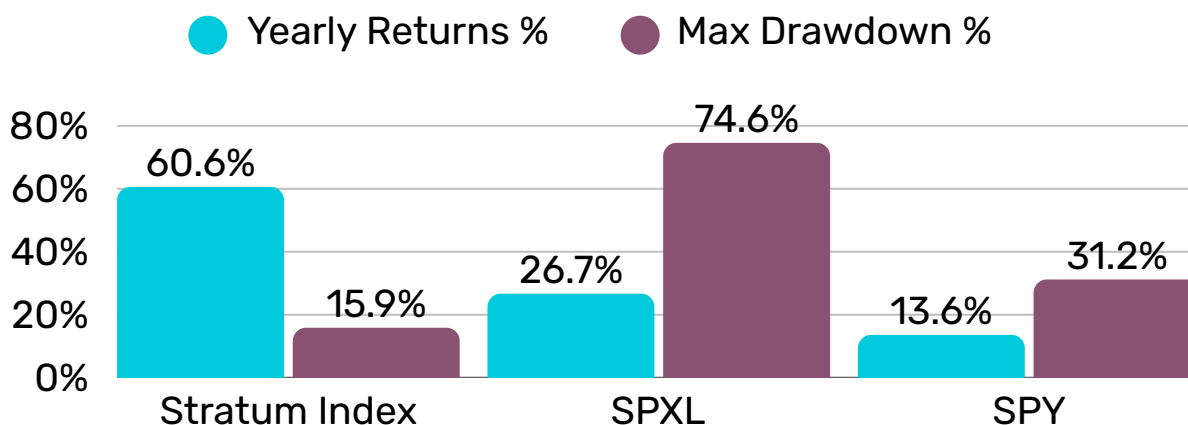
In the summer of 1831, a massive eruption from the Zavaritskii volcano, located in the Pacific Ocean, released vast amounts of sulfur gas into the atmosphere. The resulting haze tinted the sun green and purple. Reduced solar radiation cooled much of the Northern Hemisphere by roughly 1°C, triggering widespread crop failures and famine.

On the other side of the globe, German composer Felix Mendelssohn was traveling through the Alps and witnessed the effects of the eruption firsthand. In his journal, he recorded the abrupt shift in climate, writing, “it is as cold as in winter, there is already deep snow on the nearest hills” (Wizevich, 2025).

Forecasting the stock market is like forecasting the weather—both rely on historical data and shifting variables. While neither can offer certainty, they provide ranges of probable outcomes within their unpredictability. Snow in the summer can be quite rare depending on the geography.

The **Stratum Index** applies this principle by balancing risk and reward in anticipation of unforeseen events. In backtests since 2013, the Stratum Index delivered a 60.6% annualized return after fees with a Sharpe ratio of 2.49, outperforming SPY (13.6% return, 0.84 Sharpe) and SPXL (26.8% return, 0.55 Sharpe). While adapting to market shifts and avoiding major drawdowns such as Volmageddon, the COVID crash, and the SVB collapse.

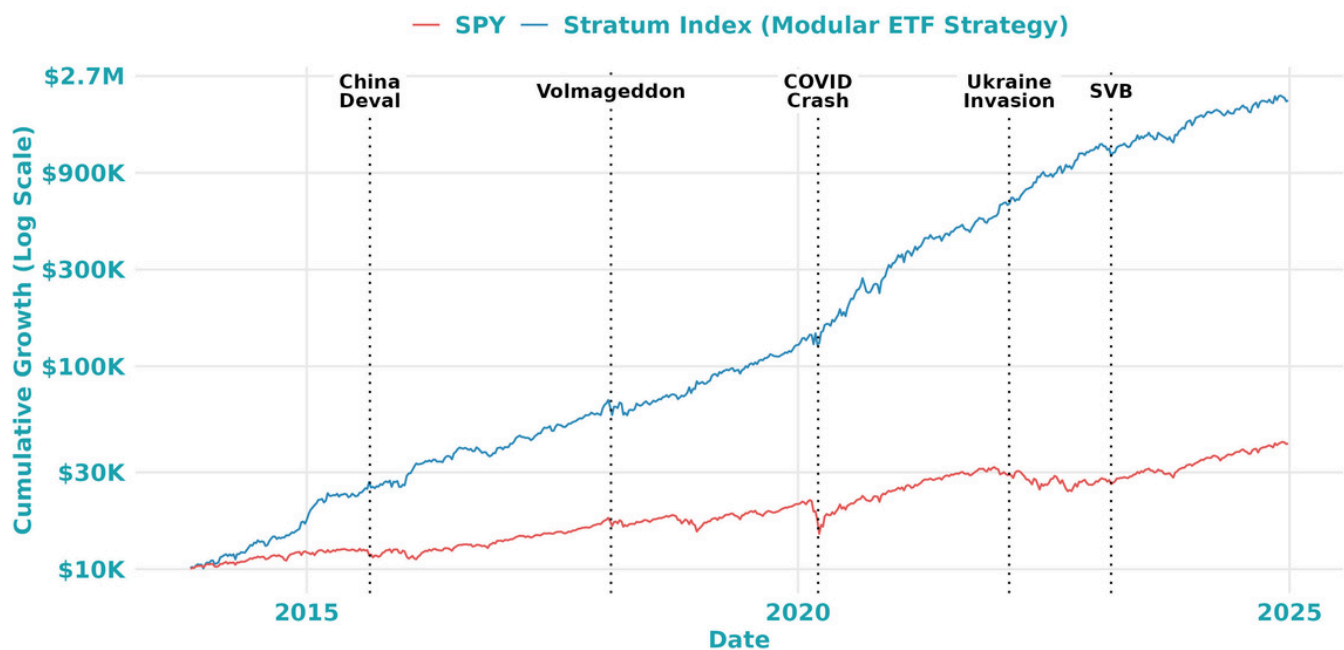
Stratum Index (Oct 25, 2013 – Dec 27, 2024)



A Modular Approach to the Momentum Strategy Design

The Stratum Index is a systematic, rules-based ETF strategy that trades weekly. Using a modular framework where multiple algorithms independently select ETFs, it reduces overfitting, hindsight bias, and trading costs. This results in a diversified portfolio with superior risk-adjusted returns. **Over 11 years, the Stratum Index would have returned 204.9x the initial value, compared to just 4.17x for a simple buy-and-hold SPY investor.**

SPY vs Stratum Index – Log Growth (Jun 20, 2013 – Dec 27, 2024)



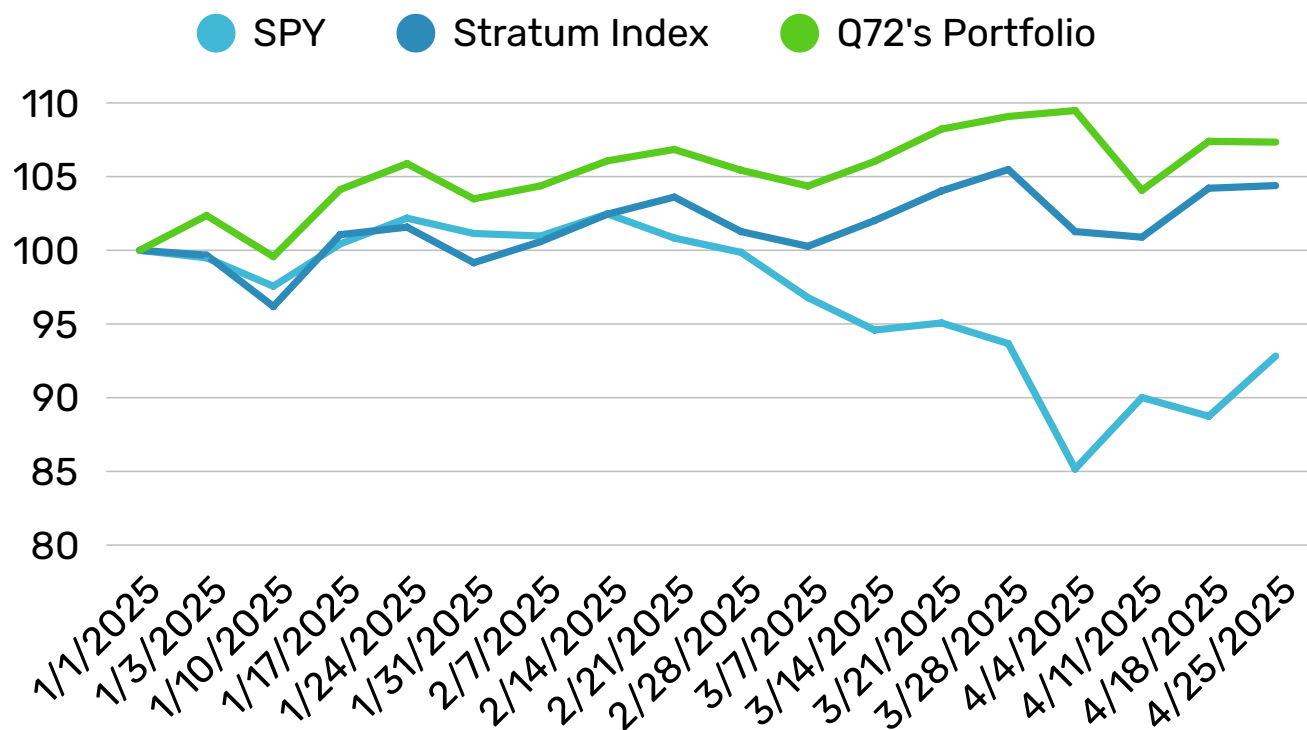
Strategy	Annualized Returns	Annualized Sharpe	Max Drawdown	Annualized Std Dev.	Total Returns	β
Stratum Index	60.6%	2.49	15.88%	24.4%	20,492%	.77
SPY ETF	13.6%	0.835	31.8%	16.2%	417%	1.0
SPXL ETF	26.8%	0.549	74.6%	48.9%	1,457%	3.02

Out of Sample Results

The early 2025 period offered a valuable live test of the Stratum Index’s discipline. As markets weakened through March, **SPY fell**, reflecting a broad equity drawdown. In contrast, **Q72's Live Trades climbed**, a striking divergence that underscored the model’s defensive rotation and adaptive posture.

By shifting toward Treasuries and gold during this phase, the system avoided the worst of the volatility and preserved gains. This live performance provided a reassuring confirmation that the model’s protective mechanisms function as designed under real market stress.

Live Validation: Stratum Index Avoids Early-2025 Drawdown



Disclaimer:

Live trade data reflects executions based on the model signals but may differ from backtested results due to timing, slippage, and transaction costs. Past performance is not indicative of future results. All investing involves risk, including the possible loss of principal. The model and related research are not investment advice and should not be relied upon to make financial decisions.

Algorithmic Trading Challenges



Financial markets, shaped by human behavior, are prone to recurring follies. For centuries, crashes have stemmed from speculative bubbles, fueled by overconfidence and flawed assumptions.

A cautionary parallel is the South Sea Bubble of 1720, where rampant speculation led to a catastrophic market collapse. Sir Isaac Newton—brilliant mathematician and inventor of derivative calculus—fell prey to the frenzy, losing £20,000 after reinvesting at the bubble's peak. Adjusted for inflation, his loss would amount to millions today.

His reflection, *"I can calculate the motions of the heavenly bodies, but not the madness of men,"* underscores the enduring challenge of predicting market behavior. Just as Newton misjudged the power of speculation, modern trading—no matter how sophisticated—often fails to anticipate herd mentality, abrupt shifts, and the deep irrationality that still governs financial markets.

"I can calculate the motions of the heavenly bodies, but not the madness of men." - Sir Isaac Newton

Data Mining Challenges

Efforts to time financial markets and identify price trends have long divided practitioners and academics, with the debate hinging on whether patterns in past data can truly predict future outcomes. Before the 2000s, most academics dismissed market timing as futile, exemplified by Malkiel's (1995) critique of technical analysis, which argued that such methods added little value beyond randomness.

However, Brock et al. (1992) shifted perspectives by applying 26 technical trading rules to the Dow Jones Industrial Average (DJIA) from 1897 to 1986. Their robust methodology accounted for data-snooping bias, used a long historical dataset, and demonstrated potential support for technical strategies. Yet, follow-up studies like Fang, Jacobsen, and Qin (2013) found poor out-of-sample performance for these same rules, raising questions about their reliability.

The challenges of data mining came into sharper focus with Bajgrowicz and Scaillet's (2012) monumental effort to evaluate 7,846 trading rules on the DJIA from 1897 to 2011. Using the false discovery rate (FDR) to correct for data-snooping bias, they showed that investors could not have identified the best-performing rules in advance. Introducing transaction costs eliminated any remaining profitability.

Similarly, Fang, Qin, and Jacobsen (2014) tested 93 market indicators on S&P 500 data and found that none outperformed a simple buy-and-hold strategy after accounting for costs. These findings underscore the inherent challenges of data mining, where the search for meaningful patterns often leads to overfitting or chasing noise disguised as signal. Such outcomes reinforce the value of simple, robust strategies like absolute momentum, as highlighted by Antonacci (2014, pp. 131–132), which prioritize enduring principles over fleeting statistical curiosities.



Momentum: The Premier Anomaly

Stock movements reflect patterns shaped by investor behavior and fundamentals. The S&P 500 selects the top 500 U.S. companies by market cap, favoring firms with sustained growth. Recurring deposits from retirement accounts into these stocks further amplify returns, creating reliable yet semi-predictable growth trends. These contributions are intentional, not random, driving capital into these companies.

This highlights the market's semi-random nature, where factors like earnings, industry performance, and geopolitical events create impacts that are semi-predictable yet inconsistent. News—a subjective force—might drive sharp movement in a stock one week and have no effect the next.

Amid this, the momentum effect stands out as one of the most robust and widely studied phenomena in financial markets, with evidence spanning various asset classes and historical periods. Research, including the foundational work of Jegadeesh and Titman (1993, 2001), has validated the predictive power of momentum, both in relative strength—where an asset's performance relative to its peers predicts its future performance—and in absolute momentum, where an asset's own past returns forecast its future performance.

Absolute momentum, which measures an asset's excess return over a specific look-back period, has shown strong applicability across asset classes such as commodities, equity indices, bond markets, and currency pairs, even back to the early 1800s (Geczy and Samonov, 2012; Hurst, Ooi, and Pedersen, 2012; Antonacci, 2014).

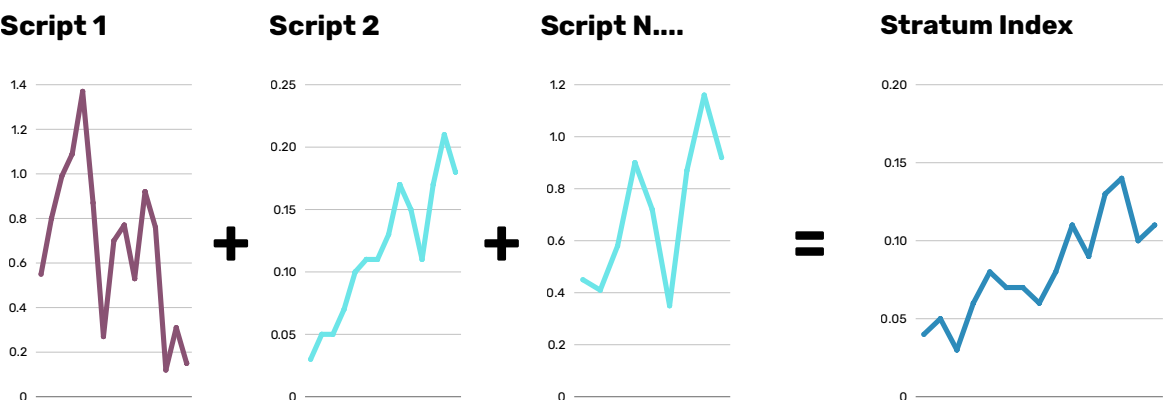
Profiting from the 'Madness of Men'

Momentum investing thrives on the "madness of men," despite ongoing debates about its underlying causes. Behavioral explanations, such as anchoring, herding, and the disposition effect, suggest that **cognitive biases fuel momentum profits**. These biases lead investors to underreact to new information, overreact during trends, and mishandle winning and losing investments. Additionally, risk-sharing mechanisms and structural market dynamics, as highlighted by Brown and Jennings (1989) and Zhou and Zhu (2014), offer further insights into the persistence of momentum, blending human psychology with market mechanics (Antonacci, 2014, pp. 153–154)."

Modular Script Architecture

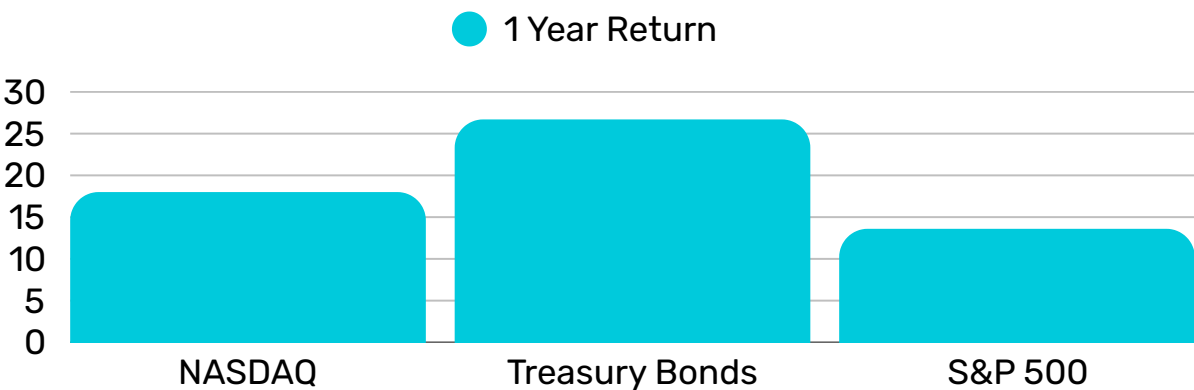
The Stratum Index consists of multiple algorithms that measure relative and absolute momentum across varying timeframes. Script 1 might allocate 10% to an equities ETF, while Script 2 might allocate 10% to a defensive ETF, and so on. The final strategy combines the outputs of all the scripts, resulting in a balanced and diversified portfolio.

Example Allocation for the Stratum Index



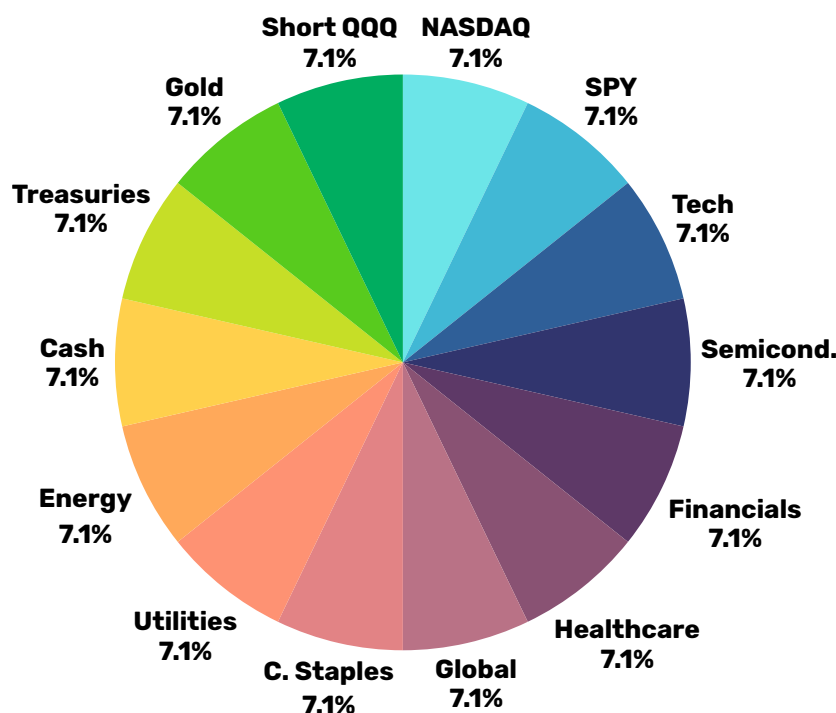
Methodology

Each script analyzes historical performance across a given time series and a selection of ETFs. Script 1 may not have the same universe of ETFs to choose from as Script 2. This approach captures short-term shifts, medium-term trends, and long-term market cycles. For instance, in the chart below showing yearly returns for three sectors, a given script might allocate to Treasury Bonds if they outperform SPY and QQQ on a year-over-year basis.



Tactical Portfolio Composition

By combining outputs from multiple rules-based algorithms, the Stratum Index allocates a percentage of total assets to tactical positions. For example, one algorithm might select Gold, another Utilities, and another the S&P 500—each behaving differently for distinct reasons, ensuring a balanced and adaptive approach.



Cash Allocation:

At least 8.36% of the portfolio is always invested in the 3-month Treasury Bill ETF (BIL), serving as a cash-equivalent anchor.

Trading Frequency:

Weekly trade signals computed from adjusted Friday closes.

Portfolio Limits:

- Holds 3 or more ETFs at all times.
- Growth ETF allocation may rise to 75%.
- Stalwart ETF allocation may rise to 58%.
- Defensive ETF exposure may rise to 100%.

Leverage:

- Composed of ETFs with leverage ranging from 100% (e.g., BIL) to 300% (e.g., SPXL).
- Average weekly leverage over 11 years is 228%.

The Business Cycle

A key contribution to the modular script architecture is State Street's business cycle framework, which analyzes decades of market sector relationships across economic cycles. For example, during recoveries, sectors like Consumer Discretionary often outperform the broader market. These historical relationships serve as crucial data points that inform the Stratum Index's strategic allocations.

State Street's Business Cycle framework, based on the Conference Board's Leading Economic Index (LEI) introduced in the 1960s, categorizes economic activity into four phases: Recession, Recovery, Expansion, and Slowdown. By integrating Kenneth French's data, it analyzes sector performance across seven recessions, 12 expansions, and 11 slowdowns using metrics like average returns and hit rates (periods of outperformance).

- **Recession:** The LEI troughs, signaling contraction. Consumer Staples, Utilities, and Health Care thrive with 86%-100% hit rates.
- **Recovery:** The LEI rebounds, signaling growth. Consumer Discretionary and Real Estate lead with 57%-86% hit rates.
- **Expansion:** The LEI rises above trends, driven by demand and profits. Technology and Financials excel with 82%-91% hit rates.
- **Slowdown:** The LEI peaks as growth slows. Health Care and Consumer Staples perform defensively with 73% hit rates.

By combining LEI cycles with sector data, State Street offers insights for constructing portfolios tailored to economic conditions. (Bartolini et al., 2019)

Methodology

By examining key sectors and their relative performance, we can make high probability educated guesses about the economy's current phase.

For instance, if the Utilities sector outperforms Technology, it may indicate an approaching recession. However, such indicators are not definitive; they could signal de-leveraging or a shift in investor preference from high-growth sectors like the Nasdaq to more stable options like Utilities.

Selection Criteria

Selection is based on both 12-month rolling correlations and intentional diversification—some scripts deliberately exclude assets included in others. This approach reduces redundant exposure, enhances diversification, and maintains balanced risk without overfitting. Roughly 55% of the portfolio follows a 65/30/5 allocation across a primary asset, secondary asset, and 5% allocated to cash. Asset order adjusts with market dynamics—for example, QQQ and TLT might be held at 65/30, but in a high-volatility environment, that could shift to TLT and GLD.

Name	Ticker	SPY	QQQ	XLK	XLV	XLU	TLT	GLD	PSQ
SPDR S&P 500 ETF Trust	SPY	1	0.92	0.91	0.8	0.51	-0.09	0.09	-0.9
Invesco QQQ Trust	QQQ	0.92	1	0.97	0.68	0.41	-0.07	0.06	-0.99
The Technology Select Sector SPDR ETF	XLK	0.91	0.97	1	0.64	0.41	-0.05	0.04	-0.97
The Health Care Select Sector SPDR ETF	XLV	0.8	0.68	0.64	1	0.49	0.13	0.13	-0.68
The Utilities Select Sector SPDR ETF	XLU	0.51	0.41	0.41	0.49	1	0.22	0.22	-0.4
iShares 20+ Year Treasury Bond ETF	TLT	-0.09	-0.07	-0.05	0.13	0.22	1	0.26	0.04
SPDR Gold Shares	GLD	0.09	0.06	0.04	0.13	0.22	0.26	1	-0.06
ProShares Short QQQ	PSQ	-0.9	-0.99	-0.97	-0.68	-0.4	0.04	-0.06	1

Correlation is not Causation

Correlation reflects how assets tend to move in relation to one another, but it doesn't guarantee consistent behavior. Combining assets with varying correlations builds portfolio resilience—at the cost of total expected returns, which is the core premise of hedging. This positions the Stratum Index to perform across a range of market environments.

A correlation matrix measures how assets move in relation to each other, with values ranging from -1 to 1:

- 1.00 = Perfect positive correlation (move together)
- 0.00 = No correlation (independent)
- -1.00 = Perfect negative correlation (move in opposite directions)

Turnover & Liquidity

Early versions of the Stratum Index allowed ETFs with only a few thousand shares of daily volume. Most were workable, but during stress periods bid-ask spreads widened sharply, increasing turnover costs. To reduce this drag, we removed higher-friction positions such as LTL and UCC.

Some funds remain essential. UPW, trading roughly 9,300 shares daily, stays in the Index because utilities provide a unique defensive anchor, and more leveraged alternatives have not shown better risk-adjusted results in backtests. Because ETFs use a creation and redemption mechanism tied to the underlying index, share volume is less restrictive than it would be for fixed-supply assets like individual stocks.

ETF Selection Rules for the Stratum Index

- **Liquidity:** ETFs should trade thousands of shares daily (ideally millions).
- **Leverage:** Prefer 2–3x ETFs; exclude 3x if history is less than 10 years.
- **Spreads:** After-hours bid-ask spreads should be <1% (ideally <0.1%).
- **Turnover:** ETFs with high frictions may be excluded.
- **Sectors:** Unique exposures (e.g., UPW for utilities) are retained despite lower liquidity.

Turnover as Risk Management

On an average week, 22.5% of the portfolio changes hands. That equates to ~11.7× annual turnover and an average ETF holding period of 2.25 weeks.

- **Weekly turnover: 22.5% of the portfolio**
- **Annualized turnover: 11.7×**
- **Average ETF holding period: 2.25 weeks**

The Stratum Index's cadence is systematic and repeatable, frequent enough to sidestep crashes and stay aligned with momentum, yet deliberate enough to remain practical for real investors.

Modeling Trading Costs

Tiingo's adjusted total-return data use market prices, adjusted for dividends, splits, fund-level expenses, and corporate actions, consistent with CRSP-style total-return methodology. These adjustments capture the performance of holding each ETF, they assume ideal execution at the National Best Bid and Offer (NBBO), the midpoint between the bid and the ask.

The Stratum Index runs on a Friday-to-Friday cycle, signals are computed from Friday closing data, trades are executed at Friday's close, and performance is measured Friday close to Friday close. To approximate real execution, we add a small slippage adjustment for spread crossing, after hours fills, and routing latency, reflecting the friction of weekly rotation during volatility or thin liquidity. The Stratum Index incorporates a modeled slippage of 0.18% at 22.5% weekly turnover.

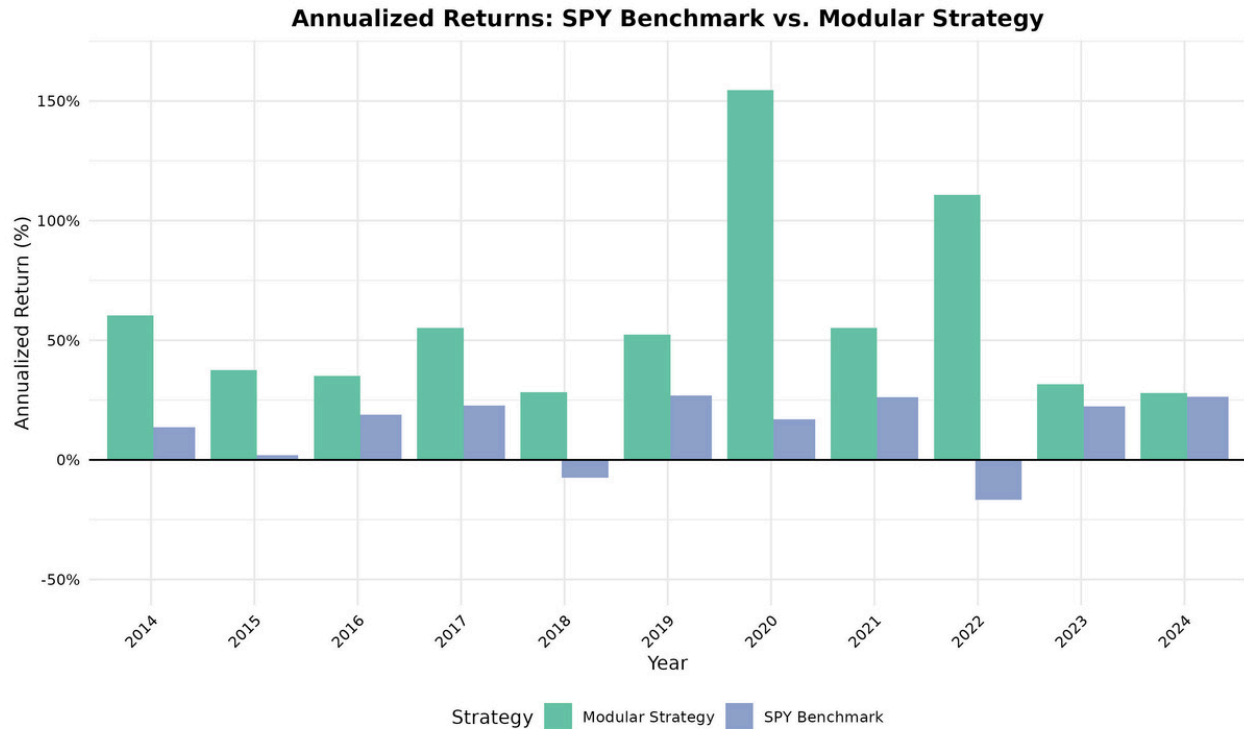
On a pre-slippage basis, the strategy produced 64.0% annualized returns, a 15.6% maximum drawdown, and a 2.70 Sharpe ratio. Including the trading-cost assumptions reduces returns modestly, the strategy's behavioral rotation edge and structural efficiency remain intact.

$$\text{Cost (per week)} = \text{Turnover} \times \text{Slippage Rate}$$

Annualized Compounded Returns	Slippage	Max Drawdown	Portfolio Turnover Rate	Annualized Drag Per Year
64.0%	.00%	15.6%	22.5%	0%
63.1%	.05%	15.6%	22.5%	0.9%
62.1%	.1%	15.9%	22.5%	1.9%
60.2%	.2%	15.9%	22.5%	3.8%
58.4%	.3%	16.1%	22.5%	5.6%

Market Regimes

Regime Name	Start Date	End Date
Post-2012 Bull (Slow, Steady)	1/1/2013	5/31/2015
2015 Correction	6/1/2015	2/29/2016
Early 2016 Rebound to 2017 Rally	3/1/2016	12/31/2017
Jan–Feb 2018 'Volmageddon'	1/1/2018	2/28/2018
Post-Volmageddon Recovery	3/1/2018	9/30/2018
Q4 2018 Selloff	10/1/2018	12/31/2018
2019 Bull Continuation	1/1/2019	2/20/2020
COVID Crash	2/21/2020	3/23/2020
COVID Rebound / Stimulus Rally	3/24/2020	12/31/2021
2022 Bear / High Inflation	1/1/2022	10/15/2022
Q4 2022 Stabilization to 2023	10/16/2022	12/27/24



The 2020 COVID Crash

Timeframe: February 21, 2020, to March 27, 2020

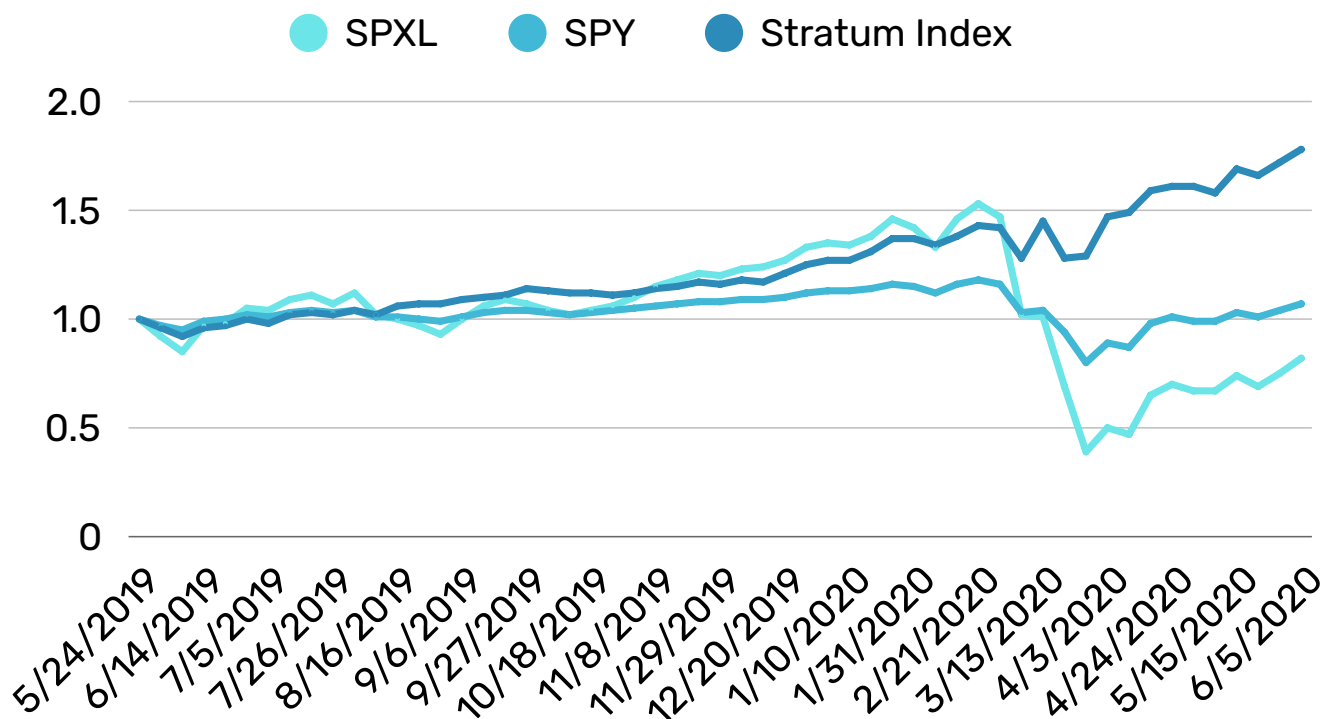
Stratum Index Performance During COVID-19 Market Turmoil:

- **Phase 1 – Initial Stock Crash (Feb 21–Mar 6, 2020):** The Stratum Index declined 2.01%, demonstrating resilience during the early equity selloff.
- **Phase 2 – Treasury Bond Crisis (Mar 9–Mar 18, 2020):** After gaining 12.6% from early bond positioning, the strategy fell 10.4% during the sudden Treasury market dislocation, reflecting systemic stress across asset classes.

Benchmark Comparisons:

- **Stratum Index: MaxDrawdown of 12.1%** during the broader market downturn.
- **SPY (S&P 500 ETF): MaxDrawdown of 31.8%** during the broader market downturn.
- **SPXL (3x Leveraged S&P 500 ETF): MaxDrawdown of 74.6%**, illustrating the amplified risk of leveraged exposure.

Performance Comparison During the 2020 COVID Crash



2018 'Volmageddon': A Challenge for the Stratum Index

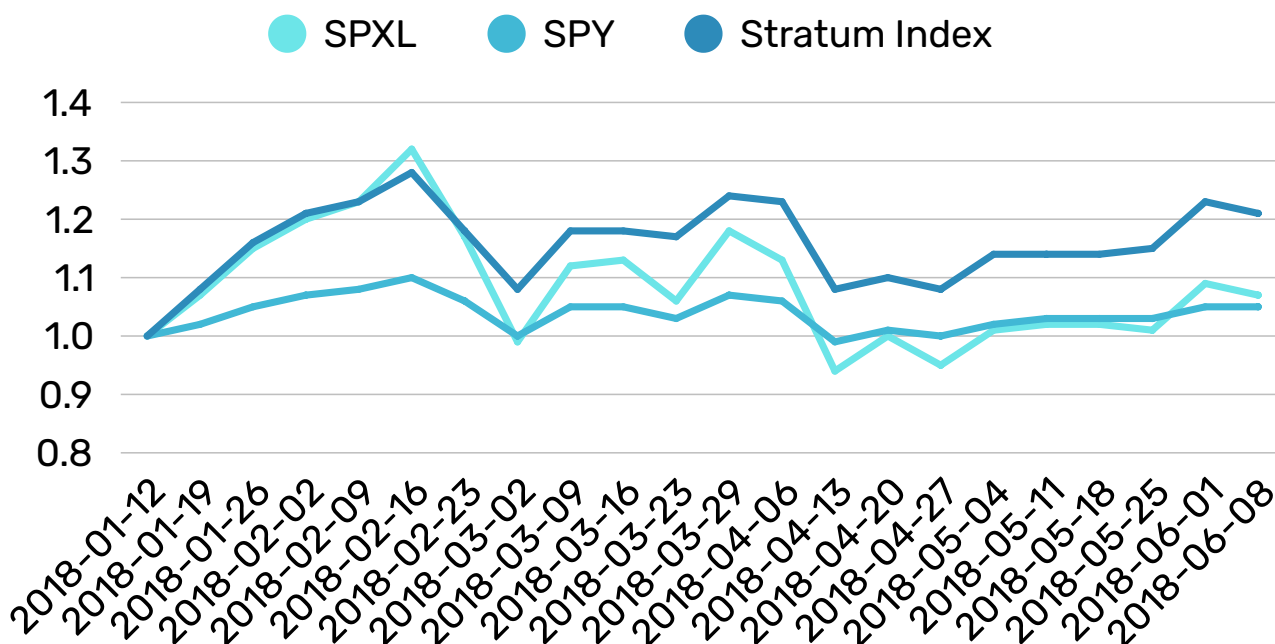
Timeframe: January 12, 2018, to June 8, 2018

The Stratum Index showcased its adaptive approach by using tactical allocation and dynamic sector adjustments to navigate flash crashes and minimize volatility. *However, like many momentum strategies, it is not immune to whipsaw effects—sharp market reversals that can temporarily reduce its effectiveness and highlight a key weakness in such approaches.*

Comparative Performance:

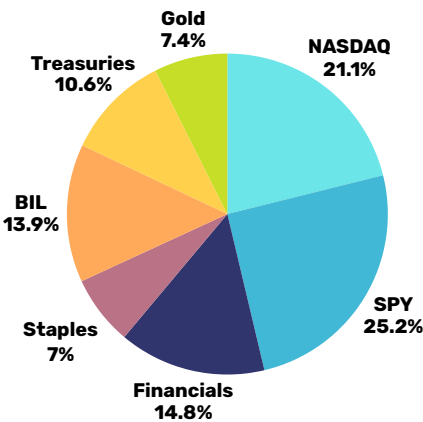
- **Stratum Index: MaxDrawdown of 15.9%**
- **SPY (S&P 500 ETF): MaxDrawdown of 9.6%**
- **SPXL (S&P 500 ETF): MaxDrawdown of 28.5%**

Performance of the Stratum Index: 2018



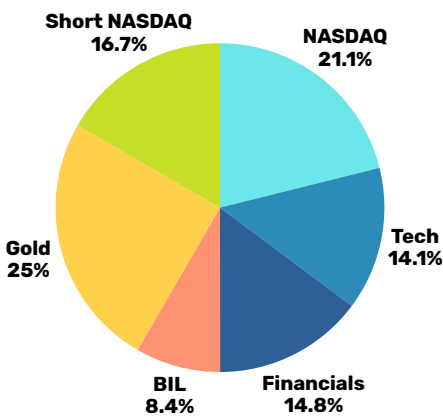
Starting February 2, 2018, without prior warning, and just before the significant VIX spike, the Stratum Index was strategically allocated across a mix of offensive and defensive sectors, including 13.9% in Cash, 10.6% in Treasuries and 7.4% Gold.

Allocation of the Stratum Index Feb 2, 2018



By the week of March 2, 2018, allocations had shifted to 16.7% shorts, 8.4% Cash, and 25% Gold, highlighting the algorithm’s tactical hedging capabilities. Notably, bonds underperformed during ‘Volmageddon,’ and the algorithm had already reallocated assets accordingly. Activating under high-probability conditions. Had the market continued to decline, the algorithm would have progressively adjusted further to safeguard the portfolio.

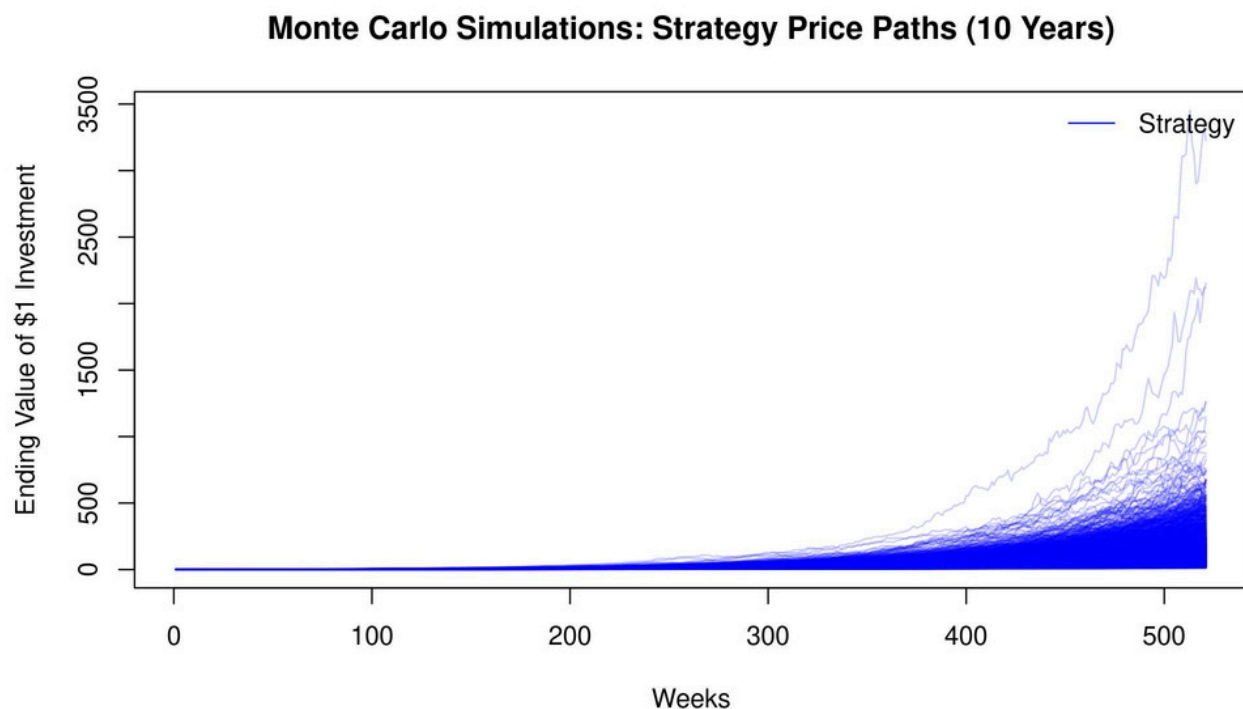
Allocation of the Stratum Index Mar 2, 2018



10-Year Monte Carlo Simulations

We ran 3,000 Monte Carlo simulations using bootstrapped returns, a method that resamples actual weekly data with replacement. This means each simulated path is built by randomly drawing from the strategy's real historical returns—some weeks may appear multiple times, others not at all. The advantage is realism: bootstrapping preserves the true sequence of volatility spikes, drawdowns, and fat tails that define markets.

10-Year Monte Carlo (Bootstrap): Percentile Breakdown of Strategy Returns



Monte Carlo Simulations: Analyzing 10-Year Performance

- 3,000 Monte Carlo simulations with replacement covering a 10-year period.
- Results grouped into deciles, with each decile representing the average performance of 300 simulations.
- Bottom 10% (Decile 1): Average Compound Annual Growth Rate (CAGR) of 40.88%
- Top 10% (Decile 10): Average CAGR of 83.4%

10-Year Monte Carlo Simulation (Bootstrap): Metrics by Return Percentile

Monte Carlo Simulation Summary by Percentile

Percentile	Total Return	Avg Drawdown	Annual Return	Sharpe Ratio	Win Percent
P1	3068	27.4%	40.8%	1.57	61.4%
P2	5075	25.2%	48.3%	1.79	62.5%
P3	6807	24.0%	52.7%	1.92	63.2%
P4	8477	23.7%	56.1%	2.00	63.7%
P5	10377	22.8%	59.2%	2.10	64.2%
P6	12565	22.5%	62.3%	2.18	64.4%
P7	15140	22.0%	65.3%	2.26	64.8%
P8	18505	21.1%	68.6%	2.33	65.0%
P9	24225	20.4%	73.1%	2.45	65.7%
P10	46078	19.2%	83.4%	2.70	66.9%

Bootstrap with Replacement Key Takeaway:

There is a high probability that the Stratum Index's performance – in terms of CAGR and max drawdown – would fall within the range shown in the table:

- CAGR Range: From 40.8% (P1) to 83.4% (P10)
- Avg. Max Drawdown Range: From 27.4% (P1) to 19.2% (P10)

This means that even in the lowest 10% of simulated outcomes (P1), the Stratum Index's average simulated CAGR was 40.8% over the 10-year period, accompanied by a 27.4% maximum drawdown. These results are hypothetical and for illustrative purposes only, highlighting the model's historical risk-return characteristics under randomized market conditions.

Appendix

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