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MSDS 451
Term Project – Checkpoint A
8/31/25

Introduction

With so many ETF's and Mutual Funds currently available, it's a massive market that many investors such as myself need to understand so that we can make our best judgement on which ones to invest in. It's no different then trying to buy a house and doing market comparisons and research on the house. According to ICI (Investment Company Institute) there are over 10,000 (Active and Index) Mutual Funds and ETF's with over $32,679 trillion of assets. With so many ETF's and Mutual funds, it's more important than ever to understand how they leverage modern day technologies to optimize portfolios, maximize returns, and reduce risks. Instead of going with the basic 5 assets as required by the assignment, I decided to expand my scope to 15 assets along a wide spectrum including index funds themselves. I also wanted to truly understand how our strategies that we're learning apply to modern day portfolios where it's a combination of equities, bonds, index funds, treasuries, etc. Most average investors gravitate towards the companies that make the news but there's still thousands of other assets that isn't in the news that help balance the ETF's and Mutual Funds.

Through quantitative finance and leveraging technology such as Python, it's now possible for average investors such as myself to be able to form my own investment portfolio of assets using the theories of quantitative finance and python. In the past, these two factors were limited to companies with scale, data, and teams of people. Now with improving pathetical models and technological advances, anyone can form their own portfolios.

Literature Review

While it would be any investors dream to invest in a company and hope that the company stock only goes up but that's not reality. As Markowitz (1952) points out that "if we ignore market imperfections the foregoing rule never implies that there is a diversified portfolio which is preferable to all non-diversified portfolios." Unfortunately, this is not reality. We've seen many downturns in the market that last days, weeks, months, and even years. According to Morningstar, from 1900's to 2000's there have been over 19 market crashes ranging from 19.6% to 79% decline. In Fundamental Indexation by Arnott, Hsu, and Moore (2005), they proved that their fundamental indexation strategy outperformed the S&P 500 by an average of 1.91% higher. Fundamental index investing is where a fund will re-balance the index fund portfolio based on financial measures of company size rather than stock price and serves as a complement to market-capitalization index strategies. Arnott, Hsu, and Moore re-balances their fund every year.

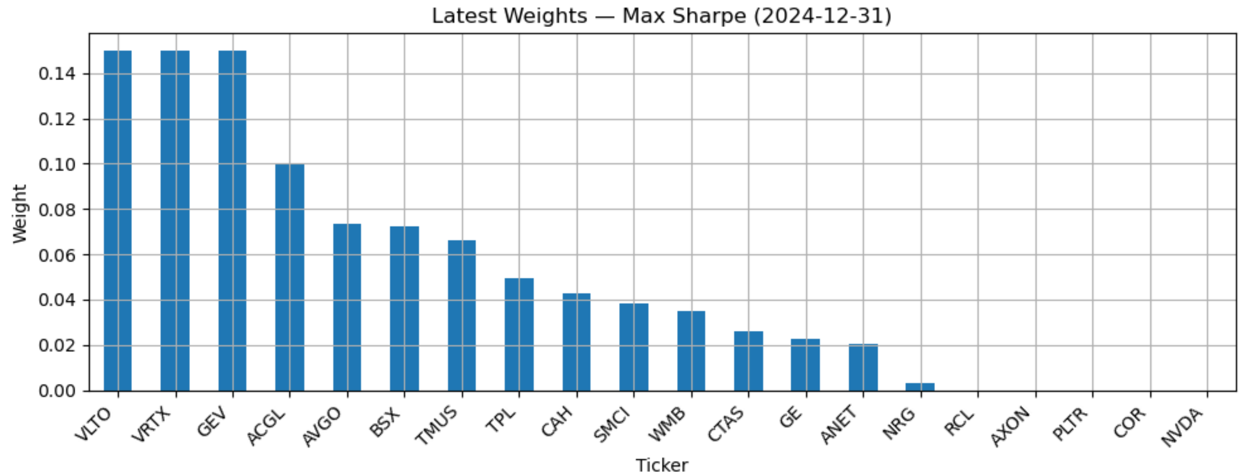
On momentum/trend, I build on Jegadeesh & Titman's seminal cross-sectional work and the broader evidence from Asness et al., Antonacci, D'Souza et al., and Gray, which show that simple trend rules can persist across assets and decades. On mean reversion, the signal construction follows the practitioner canon (Garner; Chen) and is consistent with the educational overview popularized by Algovibes. Combining momentum and mean-reversion tilts, as we do, echoes the "complementary edges" argument discussed by Velissaris.

Investment Methods/Rules Employed

It's not just the portfolios we hear about that are well balanced. According to Brinson, Singer, and Beebower (1991) 82 pension plans all had asset class weights for equity, bonds, cash, and "other" from 1977 to 1987. Their portfolio allocation was about 605 equity and 40% fixed income. Even in my role overseeing the Treasury team for my company and talking with OCIO's about recommended investments for the company, they all recommended a diverse set of investments across equities, fixed income, cash, and alternatives. Looking at Morningstar's most well balanced US-Focused Mutual Funds all include a healthy mix of equity, fixed income, and some cash. Since my portfolio comprise of index funds. ETF's on the other hand are more equity based according to Morningstar's Q2 Top Performing ETF's.

Since I did not want to "cherry pick" my assets, I decided to change my methodology from the previous models. This makes it as realistic as possible with fund managers selecting assets based on modeling data rather than having a pre-conceived list of assets in their minds. Because of the limited amount of resources and compute power, I just stuck to equity asset classes within the S&P 500. I downloaded the current list of S&P 500 stock tickers and created a csv for the model to pick up on. This was titled "universe.csv". This creates a realistic model that would be used by fund managers. The only exception is that they would most likely have additional assets such as ETF's, mutual funds, and assets on other exchanges.

To reduce the number of assets down to 20 (even number that I randomly picked), I then deployed a model to determine what 20 asset classes to include. To start, the model first limits the universe to tickers that are "live," then ranks them on a rolling window (e.g., 36 months) by a blend of Sharpe and CAGR and keeps the top 20. For those 20, it estimates expected returns and the covariance matrix. From there, the model then uses tilt expected returns and the cross-sectional signals (momentum and mean-reversion) so favored names get a slight boost. It then solves a max-Sharpe optimization with diversification constraints: total must sum to 1 and each weight is capped to ensure diversification. This ultimately produces the portfolio weights and asset classes chosen for the fund. For rebalances it applies the realized monthly returns; on rebalance months it deducts trading costs (bps × turnover), and every month it subtracts the configured expense ratio (management/other fees) to report net performance. The model output produced the following asset classes chosen for an optimized portfolio that meets the fund prospectus parameters:



Tickers	Company Name	Industry
VLTO	Veralto Corp.	Water & product-quality technologies (industrial)
VRTX	Vertex Pharmaceuticals	Biotechnology (therapeutics)
GEV	GE Vernova Inc.	Power equipment & services (generation, grid, renewables)
ACGL	Arch Capital Group Ltd.	Property & casualty insurance & reinsurance
AVGO	Broadcom Inc.	Semiconductors & infrastructure chips
BSX	Boston Scientific Corp.	Medical devices
TMUS	T-Mobile US, Inc.	Wireless telecom services
TPL	Texas Pacific Land Corp.	Oil & gas royalties & land management
CAH	Cardinal Health, Inc.	Healthcare/pharmaceutical distribution
SMCI	Super Micro Computer, Inc.	Servers, storage & data-center hardware
WMB	The Williams Companies, Inc.	Natural-gas pipelines (midstream)
CTAS	Cintas Corporation	Uniform rental & facility services
GE	GE Aerospace	Aerospace & defense (jet engines & services)
ANET	Arista Networks, Inc.	Networking equipment (switches/routers)
NRG	NRG Energy, Inc.	Independent power producer & retail electricity
RCL	Royal Caribbean Group	Cruise lines

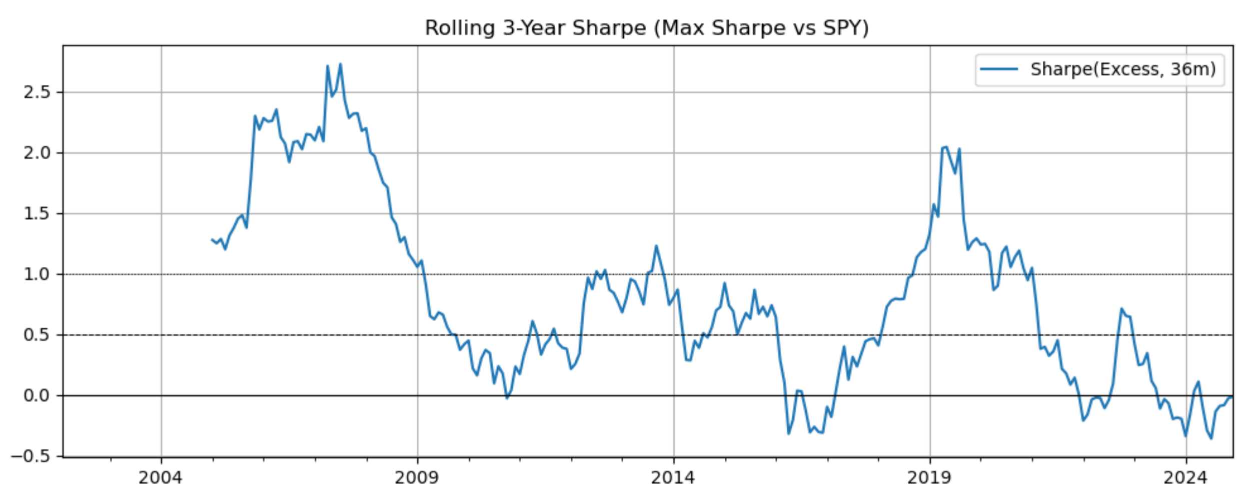
AXON	Axon Enterprise, Inc.	Public-safety technology (TASER, body cams, software)
PLTR	Palantir Technologies Inc.	Application software (data analytics/AI)
COR	Cencora, Inc.	Healthcare/pharmaceutical distribution

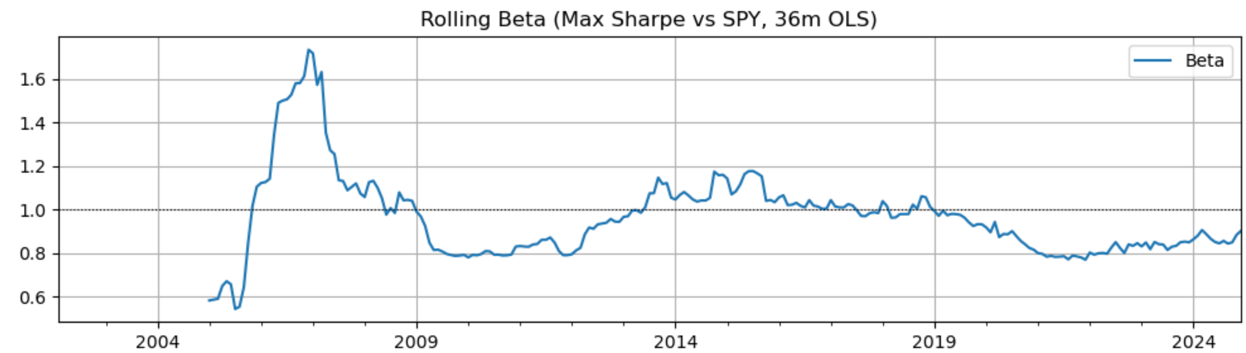
What was surprising from the model is that it produced a well-diversified list of companies across several industries. The model will then calculate performance metrics while also comparing the model against other different methods: S&P 500, Equal Weights, Max Sharpe Ratio, Minimum Portfolio Variance, Risk Parity, and Maximum Returns. The performance metrics are CAGR / AnnVol / Sharpe / Alpha / Beta / MaxDD / Calmar.

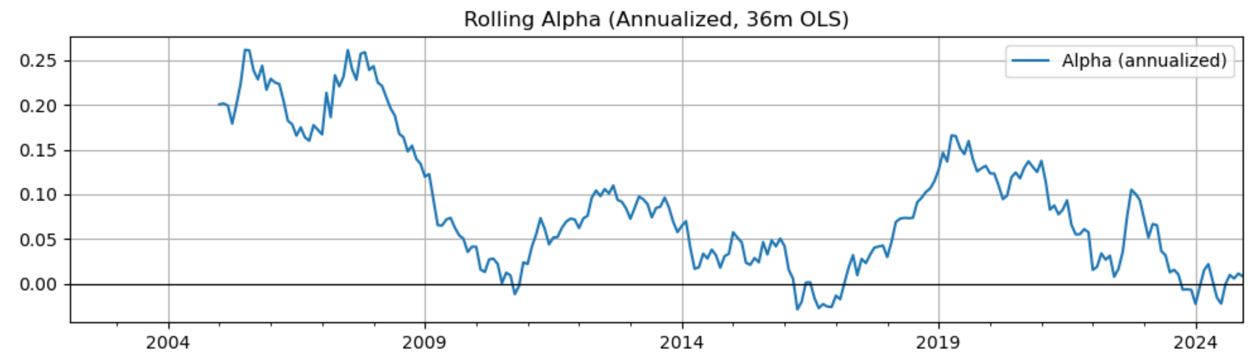
Performance Evaluation

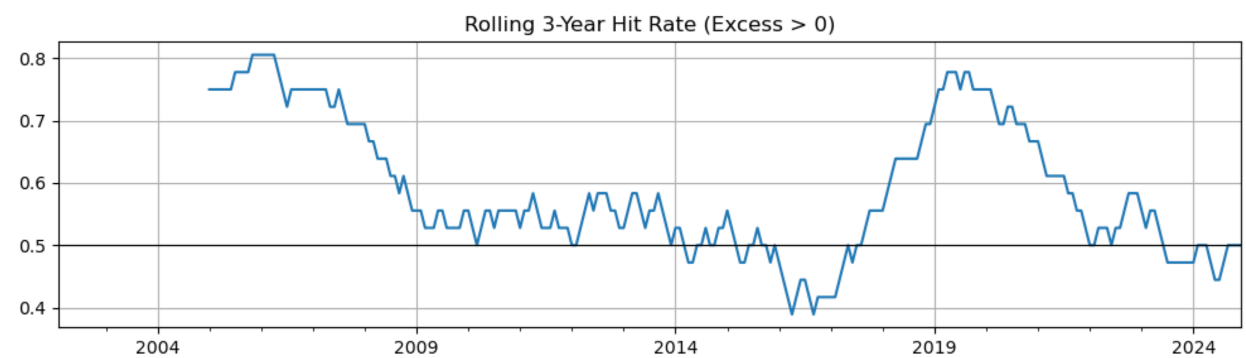
When comparing the models and performance metrics, the Max Sharpe (net) delivered ~18.6% CAGR at ~16.7% ann. vol, for a Sharpe of ~1.11. That's a substantial risk-adjusted premium to SPY (~9.5% CAGR, 14.9% vol, Sharpe ~0.63). The model carries a defensive beta (~0.84) and produced annualized alpha ~10% versus SPY. Drawdowns remain equity-like: MaxDD ≈ −49% (SPY ~−51%), yielding a Calmar ~0.38. Among the alternative model, Min-Var trades a bit of return for lower vol (~15.4%) with a small Sharpe give-up, and Risk Parity sits between them. An equal-weight live universe (EW_LIVE) improves on SPY but still trails Max Sharpe on efficiency.

Robustness checks show the edge is regime-dependent. The regime-dependency shows that the strategy's edge isn't constant and relies heavily on the market which makes sense considering all the stocks are only based on one the S&P 500 index fund. The rolling 3-year excess Sharpe is strong in 2005–08 and 2018–19, middling in 2012–16, and mostly negative in 2022–24. Rolling beta trended below 1 in recent years, so the sleeve under-participated in mega-cap-led advances, while rolling alpha also faded—together explaining recent underperformance. The hit rate (share of months beating SPY) swings from ~40–50% in softer periods to 60–80% in strong ones.

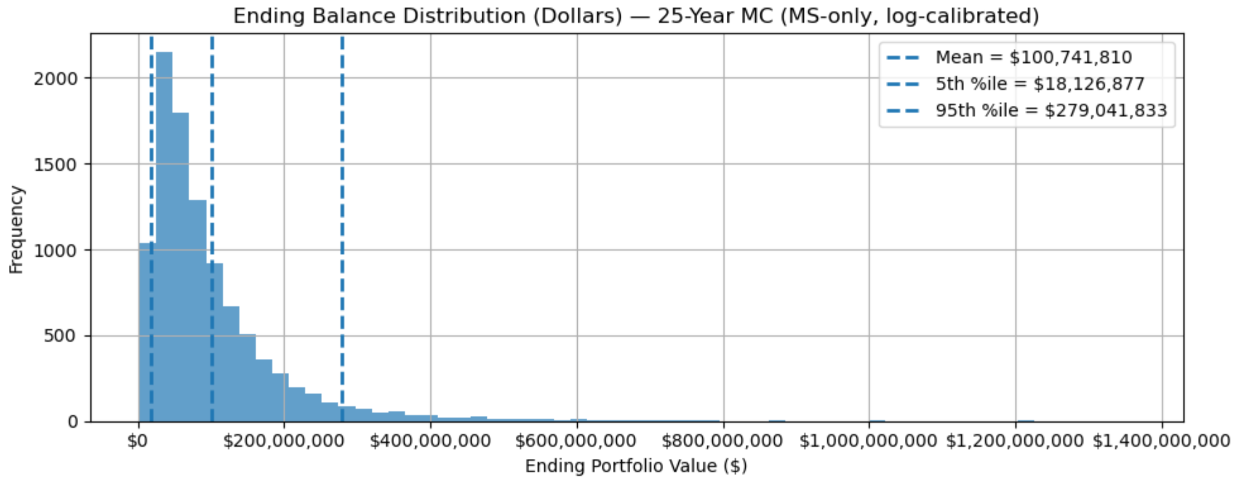


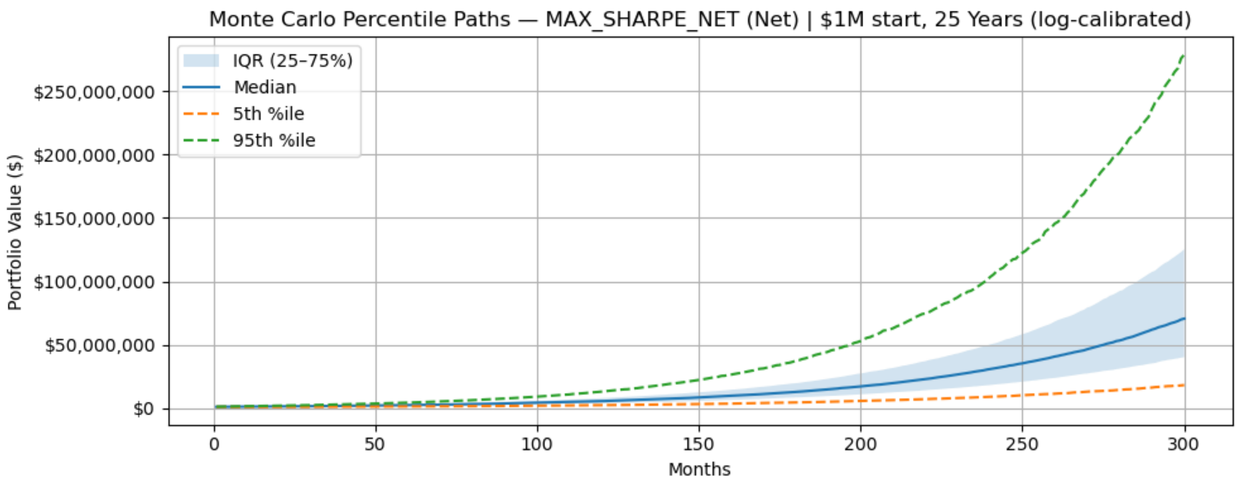




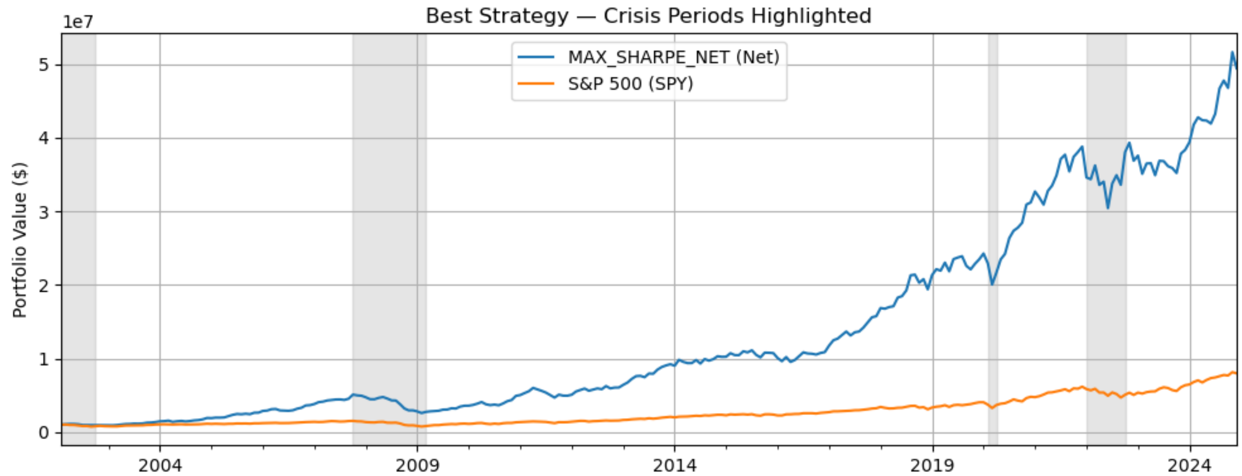


Implementation frictions are material but manageable. With the simple bps × turnover set within the model, the cumulative trading-cost drag sums to ~22% over the backtest. Fees are applied as a monthly expense ratio; plotting fee scenarios shows the expected compounding drag, but the strategy's net Sharpe remains >1. For forward-looking risk, the log-return Monte Carlo calibrated to Max Sharpe's monthly series yields a skewed wealth distribution from a $1M start over 25 years (example: mean ≈ $101M, 5th ≈ $18M, 95th ≈ $279M) which shows that the outcome in future years are wide.





Using backtesting and looking at stress testing, the portfolio still mostly outperforms benchmark S&P 500. For example, during the dot-com bubble, the CAGR on the portfolio was -9.4% vs. S&P of -26.9%. Similarly during the Great Financial Crisis, CAGR on the portfolio was -28.5% vs. S&P 500 of 33.7%. During the 2022 drawdown, the portfolio CAGR was -2.3% vs. S&P 500 of -20.9%. The COVID era was the exception where the portfolio performed poorly against the benchmark (-36.3% vs. S&P 500 -32%).



Management Recommendations

Based on the model and the realistic portion of considering all assets within the index fund S&P 500 and the performance metrics from the model, I think there's argument to justify a business, but not as a full-blown financial services firm on day one. I would want to continue to tweak the model and be able to gather more asset options so that the model is not adversely affected to only the assets within the S&P 500 index fund. I'd also want to be able to support getting live market data rather than just historical trading data. From there, I would do the following: (1) run a friends-and-family pilot under an existing platform, (2) continue to fine tune risk controls (example include but not limited to: vol-target ~12–14%, regime/TS-momentum de-risking, top-5/weight caps), and (3) operate for 12–24 months live with transparent governance (fee ledger, turnover/costs, breach log). If the portfolio performance stays close to backtest physics on the performance metrics: CAGR in the mid-teens, Sharpe ≥ 0.9, controlled turnover, and crisis behavior matches the desired overlays, then I would ultimately step up to a dedicated vehicle and brand.

If I were to join instead of starting a fund, I'd take a Quantitative Finance PM/Research Lead role (portfolio construction, risk, and model governance) and hire an operator for COO/Compliance rather than be CEO myself. The edge here is in research discipline and risk engineering. Without direct experience, being a CEO on day one also puts the fund at risk. Many times, investors will review fund managers historical performance as a proxy for how well the fund may do. If these options don't work out, then I would consider using the model to do some hobby investing.

AlphaQuant Strategies Fund

Fund Name: AlphaQuant Strategies Fund
Ticker Symbol: AQSF
Fund Type: Actively Managed Exchange-Traded Fund (ETF)

Investment Objective

The AlphaQuant Strategies Fund goal is to seek long-term capital appreciation and minimizing risks by allocating across multiple asset classes based on data-driven quantitative models.

Fees and Expenses of the Fund

The below table describes the fees and expenses that investors may pay if you buy and hold shares of the fund.

Shareholder Fees (fees paid directly from your investment)

	Investor Class	**Institutional Class**
Redemption Fee	None	None

Annual Fund Operating Expenses (expenses that you pay each year

	Investor Class	**Institutional Class**
Management Fee	0.55%	0.55%
Distribution and service Fees	0.25%	0.00%
Other Expenses	0.205	0.20%
Total Annual Operating Expenses	**1.00%**	**0.755**

Example. This Example is intended to help you compare the cost of investing in the Fund with the cost of investing in other mutual funds. The Example assumes that you invest $10,000 in the Fund for the time periods indicated and then redeem all of your shares at the end of those periods. The Example also assumes that your investment has a 5% return each year and that the operating expenses remain the same. Although your actual costs may be higher or lower, based on these assumptions your costs would be:

	1 Year	**3 Years**	**5 Years**	**10 Years**
Investor Class	$105	$344	$626	$1,558
Institutional Class	$79	$260	$475	$1,189

Portfolio turnover

Portfolio turnover is a measure of how frequently assets within a fund are bought and sold. It's calculated by either taking the total amount of new assets or the number of assets sold over a period of tine and divided by the net asset value (NAV). Since this is a new portfolio, the turnover rate is not calculated but the fund is targeting a rate of ~20% - 50%. The portfolio turnover is intended to be low to keep trading costs low for our investors.

Principal Investment Strategy

The AlphaQuant Strategies Fund seeks long-term capital appreciation while minimizing risks for investors. The fund will use a quantitative, model-driven investment strategy drawing from methodologies used by other top-tier institutional investors. The fund will allocate assets across US equities, bonds, commodities, and volatility-linked securities. The fund strategy will be centered around three core quantitative pillars:

1. **Time-Series Momentum & Regime-Based Allocation**
2. **Volatility-Targeted Risk Management**
3. **Adaptive Portfolio Optimization**

Time-Series Momentum a core fund strategy is a quantitative approach that invests in assets exhibiting positive trends within recent price history. This strategy can also be used to help predict returns based on historical trends (e.g. positive or negative). We can then use those trends to determine whether we hold or sell an asset. This strategy has been demonstrated over a 212-year span of US equity and has consistently delivered excess returns even through major market downturns (Geczy & Samonov, 2016). Not only is this method proven among US equities, but it's also been proven across other global asset classes such as stocks, bonds, commodities, and currencies (Moskowitz, Ooi & Pedersen, 2012).

In addition to the momentum trading, the fund will incorporate a regime-based strategic asset allocation framework. To help optimize for dynamic economic environments, the fund may rebalance asset classes based on their associated risk profiles in various economic regimes – growth, inflation, stagnation, and contraction (Bouyé & Teiletche 2024). The fund will use probabilistic models to identify macroeconomic regimes using data such as but not limited to GDP, CPI, credit card spending, loan delinquencies, etc.

To help stabilize the risk profiles of asset classes, the fund will deploy a volatility targeted risk management framework. Rather than having a static position, the fund will rebalance the asset allocations based on recent or forecasted volatility. This will allow the fund to implement targets at both the asset-class level and at the total portfolio level. The targets for the fund will be as follows:

	Acceptable Ranges
Annualized Volatility	10% - 20%
Sharpe Ratio	≥0.8
Maximum Drawdown	< - 75%

The last and final piece of the core quantitative pillars is Adaptive Portfolio Optimization. The fund will incorporate adaptive-robust principles to address uncertainties in the market. It will use two key elements: 1) robust optimization which helps the model guard against misestimation and

2) adaptive learning so that the model can update as new data arrives (Bhudisaksang et al., 2025). This helps protect the fund from potential overconfidence within the data while also incorporating new market data.

The fund will primarily be using technical analysis such as price momentums (identifying trends across 1M, 3M, or 12M scenario), volatility breakout, and moving average signals. The fund will also deploy a top-down macroeconomic signal to define broad exposure to various type of asset classes and at the portfolio totality. The fund will not engage in short-term speculation and is focused on long-term capital appreciation. As needed, the fund will rebalance weekly or monthly based on signal turnovers. The portfolio turnover will be constrained to minimize costs to investors and to maintain tax / trading cost disciplines.

Example of how the fund will deploy the rules for buying / selling:

Buy	**Initiate or increase position when security:**
	Has positive 1M, 3M, 6M, or 12M returns
	Has volatility under cap threshold
	Is in a supported regime
	Is one of the top signal scorers
Sell / Reduce	**Reduce or exit when:**
	Return momentum turns negative (1M, 3M, 6M, or 12M)
	Regime changes unfavorably
	Volatility risk above threshold
	Rebalancing lowers fund thresholds

While the Fund incorporates principles of long-term investing it does not follow a strict buy-and-hold strategy. Instead, the fund employs a dynamic, quantitative-based active allocation approach that responds to market conditions through signals grounded in price trends, volatility, and macroeconomic regime shifts. This provides the fund flexibility to remain invested during favorable periods while de-risking any potential impacts of drawdowns.

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