### What is our inspiration:

1. AQR
2. Renaissance Technologies

### What is our thesis:

We focus heavily on systemic investing (which is another saying for quantitative investing). This means we emphasize data-driven insights and advanced modeling techniques to construct our portfolios. Currently, we are focused on Machine-Learning-Based, Factor-Based, Statistical Arbitrage, Smart-beta, and Trend-Following Strategies. We believe that these strategies hold the greatest risk premia and allow for effective risk allocation. In addition, our strategies are developed with an emphasis in market-neutrality and maintaining the lowest level of risk with greater return. To ensure we meet the needs of our investors, we have implemented multiple strategies as risk-mitigators and multiple strategies as diversifying profiters.

### Rules:

To main a certain minimum level of risk, while also capturing the greatest risk premia, we believe that these set rules for investing into single-stock equities provide the best results:

1. **Size:**
   Only invest into mid-cap to large-cap stocks. Thus, Market-Cap for a stock must be greater than $2B in order for us to invest into it
2. **Length:**
   The stock must have at least 3 years worth of data. This ensures not only that the stock has a strong potential for lasting in the future, but it also allows us to conduct data-driven research with higher confidence.
3. **Return:**
   The strategy's cumulative much greater than or equal to the SPY benchmark index
4. **Risk:**
   Each strategy's volatility can be no more than 10% volatility, 0% risk of ruin, and no more than 2% Daily Value at Risk.
5. **Drawdown:**
   For risk premia strategies (i.e., ML Strategy), the max drawdown should be no more than 15%

### Risk Management:

#### Market & Factor Risk:

To ensure we have minimum market & factor risk, we regress all our risk premia strategies against our research multi-factor models to minimize every model's beta coefficients for each stock in our portfolio. Each beta coefficient represents a measure of exposure (either towards market or factor), and we have conducted immense multiple t-stat hypothesis testing to ensure that these factors are valid in determining risk.

#### Liquidity Risk:

Our rule of only investing into mid-cap to large-cap stocks (over $2B market cap) ensures a level of security against potential for illiquidity issues while buying or selling a stock. In addition, our other rule of trading on stocks with at least 3 years worth of data, ensures that the stock will highly likely continue to be traded for a set number of years. The reason for this confidence is that since 2008, only around 10 stocks have dropped from $2B to $0 market cap in less than a year's worth of time. The most recent one being Silicon Valley Bank.

**Model Risk:**

Our code and models have been thoroughly tested over and over again to ensure efficiency, accuracy, and efficacy. In addition, every single one of our strategies have gone through multiple out-of-sample tests (i.e., 6 month trading period of live paper trading) and stress tests (i.e., Monte-Carlo simulation). Lastly, our pool of different strategies (i.e., factor-based, smart beta, etc.) ensures diversification across strategy and within each strategy we diversify across a universe of stocks (i.e., bonds, commodities, equity, etc.). For each strategy, we also observe a diverse set of risk measures (i.e., Variance, Value at Risk, Risk of Ruin, etc.) to ensure that our strategies will meet every investor's risk tolerance.

**Operational Risk:**

All our strategies are conducted on a daily or longer interval basis. This ensures large amounts of time to check on orders placed, model predictions, etc. Additionally, each order we execute is a Market On Close (MOC) Order. This ensures that as long as the MOC order executes, the order will be placed no matter what. How do we ensure that a MOC executes? This is just a Liquidity Risk issue that we have already addressed.

**Technology Risk:**

All data is retrieved live from reliable, paid data service providers, ensuring accurate data. This data is then stored on prem and uploaded to the cloud to ensure a double layer of security against loss of data.

**Strategic Asset Allocation:**

Among our plethora of diverse strategies, we take a long-term approach. Each strategy's weight is predetermined and remains constant with little to no fluctuation (unless another strategy is added) within our portfolio for the rest of its lifetime. To determine the weight of each asset, we utilize both statistical tests and discretionary inputs.

**List of the potential strategies:**

*Highlighted are strategies of most interest to us*

**ML-Based Investing:**

Machine learning-based strategies in finance use algorithms to analyze large datasets for predicting market trends, executing algorithmic trades, managing risk, and optimizing portfolios. These strategies range from forecasting asset prices to sentiment analysis using news and social media. While offering advanced insights, they require careful management to ensure accuracy and adaptability in dynamic financial markets.

**Factor-Based Investing:**

Implementing multi-factor models that combine different risk premia such as value, size, momentum, and quality. Algorithms can be designed to weigh these factors based on historical performance, economic conditions, or risk considerations.

**Statistical Arbitrage:**
Exploiting pricing inefficiencies between pairs of securities or within baskets of stocks using mean-reversion, cointegration, or other statistical techniques. Algorithms identify pairs or groups of stocks where the price relationship is temporarily out of balance.

**Carry Trade in Forex:**
Using algorithms to identify opportunities in the currency markets where you can profit from the interest rate differentials between currencies. The strategy involves going long in high-yielding currencies and short in low-yielding currencies.

**Volatility Trading:**
Implementing strategies to capture the volatility risk premium, such as selling options or volatility indices. Algorithms can be used to time these trades based on market volatility forecasts and historical volatility patterns.

**Liquidity Provision:**
Acting as a market maker by providing liquidity through algorithmic strategies. This might involve placing buy and sell limit orders near the current market price and capturing the bid-ask spread.

**Smart Beta Strategies:**
Developing algorithms that follow smart beta strategies, which are rules-based and aim to capture specific risk factors. These can include equally-weighted indexes, fundamentally-weighted indexes, or volatility-weighted strategies.

**Event-Driven Strategies:**
Focusing on corporate events such as mergers and acquisitions, earnings announcements, or regulatory changes. Algorithms can be designed to exploit price movements or inefficiencies that occur due to these events.

**Term Structure Strategies in Fixed Income:**
Using algorithms to exploit opportunities arising from the shape of the yield curve. For example, a strategy might involve going long on short-term bonds and short on long-term bonds if the yield curve is expected to flatten.

**Global-Macro Strategies:**
Leveraging algorithms to take positions in various asset classes (equities, bonds, currencies, commodities) based on macroeconomic trends and policies. These strategies might involve complex models to interpret economic data and predict market movements.

**High-Frequency Trading (HFT):**
Engaging in very short-term trading at high speeds, often capturing tiny discrepancies in pricing. While not a risk premia strategy in the traditional sense, HFT can capitalize on short-term market inefficiencies.

**Trend-Following:**
This approach involves capitalizing on market trends using technical analysis to identify and follow the direction of asset price movements. Traders employing this method take long positions in assets trending upwards and short positions in those trending downwards. Key tools include moving averages and momentum indicators like the RSI. Trend-following can be applied across various time frames and is reliant on disciplined risk management, including stop-loss orders to protect against market volatility. While effective in capturing significant market movements, its performance may vary in markets without clear trends.

## Present Strategies:

1. **ML Strategy (ML-Based):**
   *ML stands for machine learning*
   Designed a machine learning model that relies on over 250 different factors to predict stock returns for the next day. We utilize incremental training, ensemble predictions, early-stopping, walk-forward optimization, L2 Regularization, and Minimum Gain-to-Split as parameters to reduce overfitting. Based on these predicted returns, we long and short a set number of stocks that our model believes will perform the best. Each stock is weighted equally within our portfolio. This portfolio is rebalanced on a daily interval, is long-short, and requires 0 leverage.
2. **Mrev ETF Strategy (Statistical Arbitrage):**
   *Mrev ETF stands mean-reversion etf*
   Designed a dynamic multi-factor model that calculates the s-score, which is based on the epsilon of our model. This s-score possesses a mean reverting property, and allows us to determine when certain stocks are deviating from their relationship with their corresponding ETF. Based on a given signal, we either long or short a stock, while hedging with the corresponding ETFs. This portfolio is rebalanced on a daily interval, is long-short, and requires 0 leverage.
3. **Port IMS Strategy (Smart Beta):**
   *Port IMS stands for Portfolio Inverse Macro Seasonality*
   Designed a smart beta strategy that uses a stocks inverse volatility to weight it in a portfolio. This ensures minimum volatility. In addition, this portfolio is constructed of equity, bond, and commodity ETFs to ensure another level of diversification (following the risk parity principle). To ensure greater return, we implemented systematic rules that follow seasonality rules, mutual fund flows, and macroeconomic trends to weight stocks in a better performing way. This portfolio is rebalanced on a daily interval, is long-only, and requires 0 leverage.
4. **Port IVMD Strategy (Factor-Based):**
   *Port IVMD stands for Inverse Value Momentum Defensive*
   Designed a factor-based strategy that uses three factors – Value, Momentum, and Defensive – to rank a given stock in our stock universe. After taking the average of these three ranks, we can then determine which stock to long (largest average rank) and short (smallest average rank). Additionally, we use inverse volatility to weigh each stock. This portfolio is rebalanced on a daily interval, is long-short, and requires 0 leverage.
5. **Port IV Strategy (Factor-Based):**
   *Port IV stands for Inverse Value*
   Designed a factor-based strategy that uses multiple different measures of Value rank a given stock in our stock universe. After taking the average of these factor ranks, we can then determine which stock to long (largest average rank) and short (smallest average rank). Additionally, we use inverse volatility to weigh each stock. This portfolio is rebalanced on a daily interval, is long-short, and requires 0 leverage.
6. **Port IM Strategy (Factor-Based):**
   *Port IM stands for Inverse Momentum*
   Designed a factor-based strategy that uses multiple different measures of Momentum rank a given stock in our stock universe. After taking the average of these factor ranks, we can then determine which stock to long (largest average rank) and short (smallest average rank). Additionally, we use

inverse volatility to weigh each stock. This portfolio is rebalanced on a daily interval, is long-short, and requires 0 leverage.