# Predicting S&P 500 realized volatility using mixed-frequency time series forecasting

# Our Team

## Systematic Trading

WUTIS

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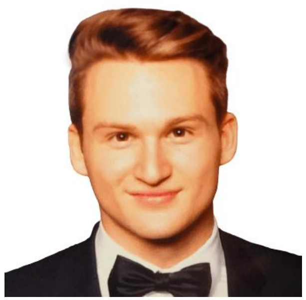

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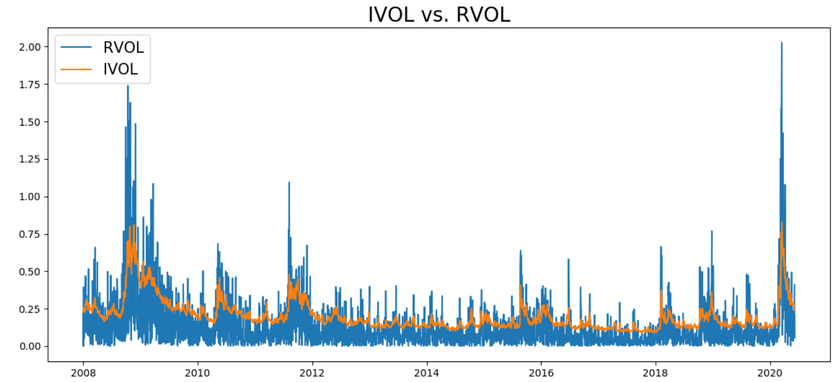
# Volatility Trading

## What it is and why we care

### Trading Volatility

- Volatility can be traded of any asset class where options exist, but the most popular volatility to trade is the VIX, which can be traded via derivatives.
- Volatility is usually traded in such a way traders collect the volatility risk premium
- VRP: the premium that can be earned by selling or buying volatility. It is the difference between IVOL and RVOL.
- IVOL: market price of volatility (VIX)
- RVOL: standard deviation of the market returns




### Deriving IVOL from the B&S Formula

Basic Formula:

$$C(S,t) = S\Phi(d_1) - Ke^{-r(T-t)}\Phi(d_2)$$

With:

$$\Phi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) \mathrm{d}z$$

$$d_1 = \frac{\ln(S/K) + (r + \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}}$$

$$d_2 = \frac{\ln(S/K) + (r - \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}} = d_1 - \sigma\sqrt{T-t}$$

### Deriving RVOL

- Several models, but no model that is clearly the best one
- We decided on testing two different approaches
- **Model 1:** GARCH-MIDAS models
- **Model 2:** Monte Carlo simulation

# Model I: Garch-Midas

## Forecasting RVOL

### GARCH-MIDAS Formula

$$\hat{\sigma}_{i,t}^2 = \tau_t * g_{i,t}$$

where

$$g_{i,t} = (1-\alpha-\beta) + \alpha \frac{\left(r_{i-1,t}\right)^2}{\tau_t} + \beta g_{i-1,t}$$

$$\tau_t = \exp\left(m + \theta \sum_{k=1}^{K} \delta_k(\omega) X_{t-k}\right)$$

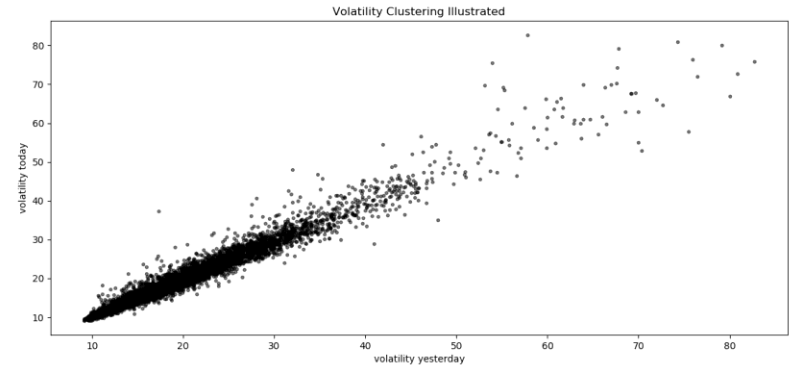
with

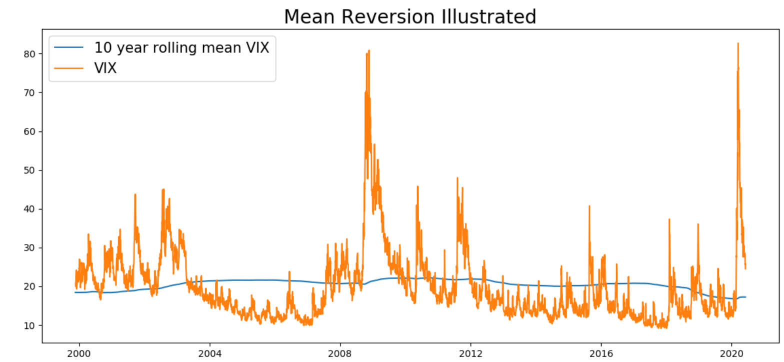
$$\delta_k(\omega) = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(j/K)^{\omega_1-1}(1-j/K)^{\omega_2-1}}$$

### Low Frequency Inputs

- Weekly
  - 5-minute intraday variance
  - National Financial Conditions Index
- Monthly
  - Industrial Production Index
  - Chicago Fed National Activity Index
  - New privately owned housing units started

### Why it works



# Model II: Monte Carlo Simulation (MCS)

## Simulating RVOL

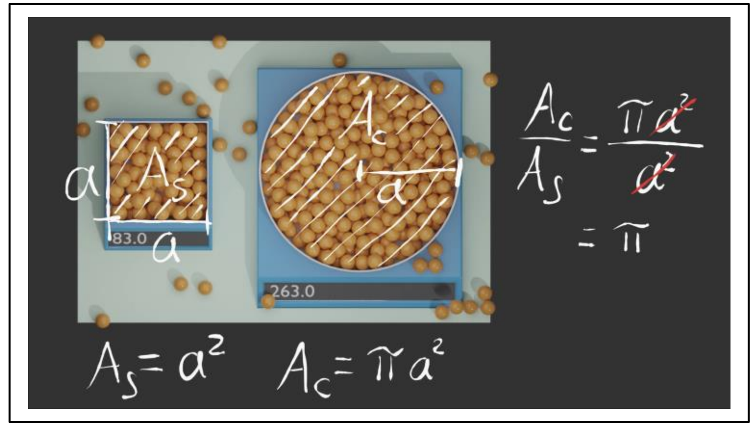
### What is the Monte Carlo Simulation and why could it be helpful?

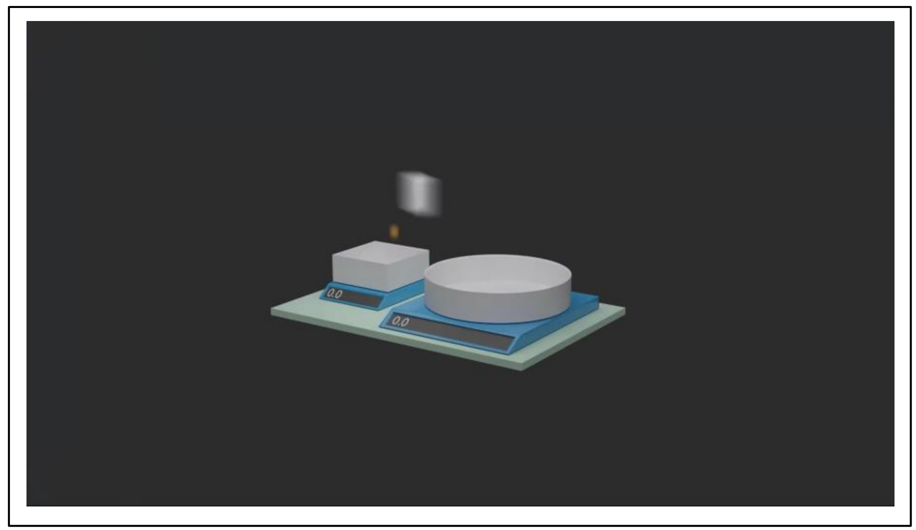
- Approximation of probabilistic problems through statistical random sampling
- Consist of a class of various computational algorithms
- Based on the law of large numbers
- Widely used for option pricing
- Not a prediction model, but rather a simulation of how the future could look like

$$\sigma^2 = [\frac{1}{N}\sum_{i}^{N}\frac{f^2(x_i)}{g^2(x_i)}] - [\sum_{j}^{N}\frac{1}{N}\frac{f(x_j)}{g(x_j)}]^2$$

### Key Takeaways

- A Monte Carlo simulation is a model used to predict the probability of different outcomes when the intervention of random variables is present
- Monte Carlo simulations help to explain the impact of risk and uncertainty in prediction and forecasting models
- The basis of a Monte Carlo simulation involves assigning multiple values to an uncertain variable to achieve multiple results to then average the results
- Monte Carlo simulations assume perfectly efficient markets



# Model II: Monte Carlo Simulation (MCS)

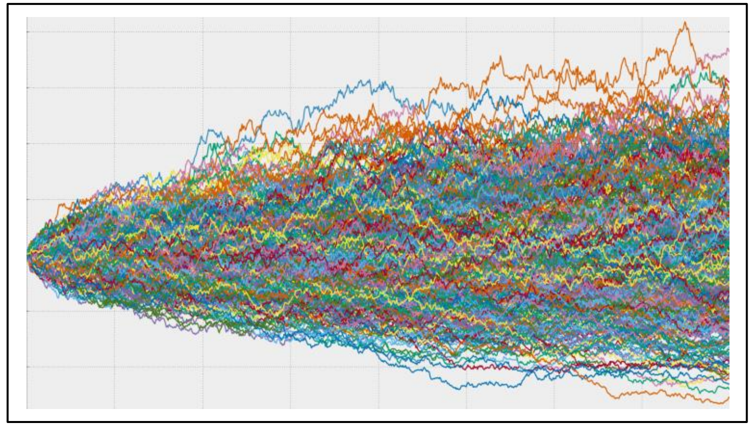
## Simulating RVOL

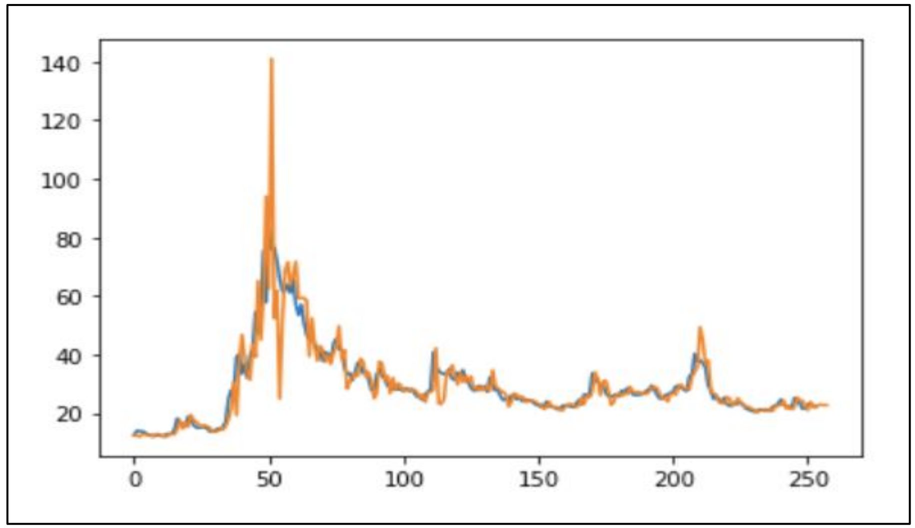
### Monte Carlo Simulation in Action

- In order to avoid mean reverted results overlong term investments:

  i. 5-day moving average on a daily-rolling basis
  ii. Computing millions of different scenarios of how the asset might move the next day
  iii. Taking the mean of those simulation and implement it

- Number of simulations each day: 1.000.000
- Can also be used as an indicator to hedge portfolios






### Some Trivial Formulas

$$Periodic\ Daily\ Return = ln\left(\frac{Day's\ Price}{Previous\ Day's\ Price}\right)$$

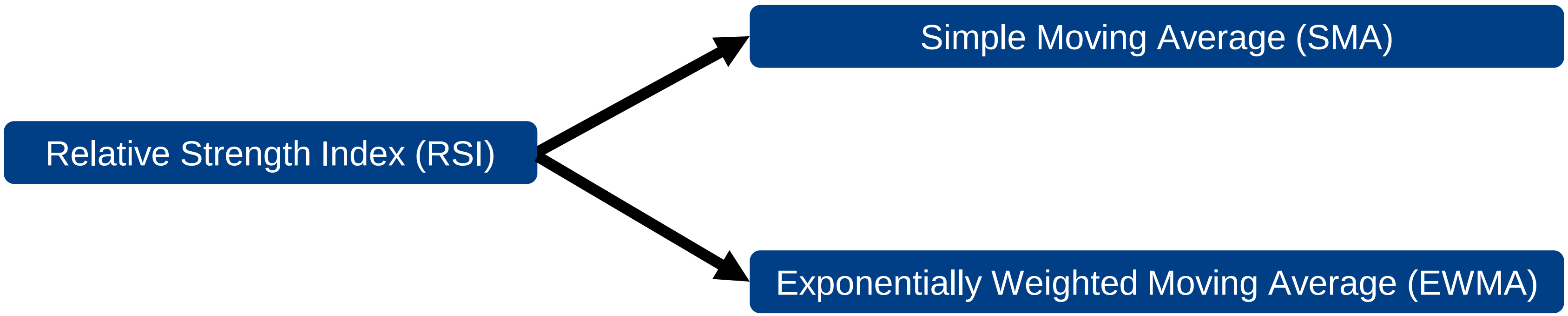
$$Drift = Average\ Daily\ Return - \frac{Variance}{2}$$

$$Next\ Day's\ Price = Today's\ Price \times e^{(Drift + Random\ Value)}$$

# Creating a Forecast – Based Indicator

## Methodology

### Basis for Algorithm




### Key points

- Inversely weighted position sizing depending on the daily RSI
- Weight calculation for Short VXX & Long VXX positions

### RSI Formulas

Upward Change

$U = X_0 - X_{-1}$

$D = 0$

Downwards Change

$U = 0$

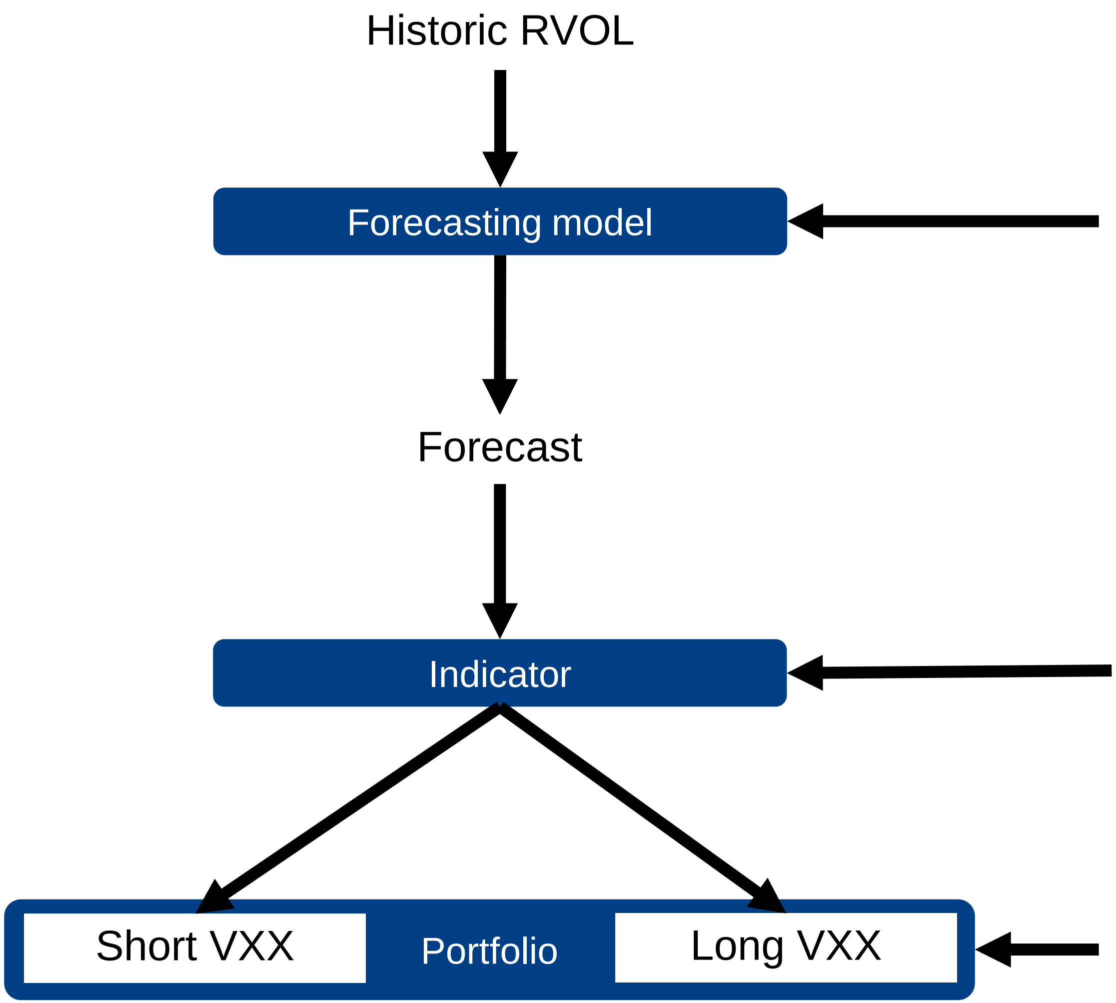
$D = X_0 - X_{-1}$

$$RS = \frac{SMA \ \& \ EWMA\ (U, n)}{SMA \ \& \ EWMA\ (D, n)}$$

$$RSI = 100 - \frac{100}{1 + RS}$$

# Backtesting Model

## Methodology




- GARCH-MIDAS
- Monte Carlo

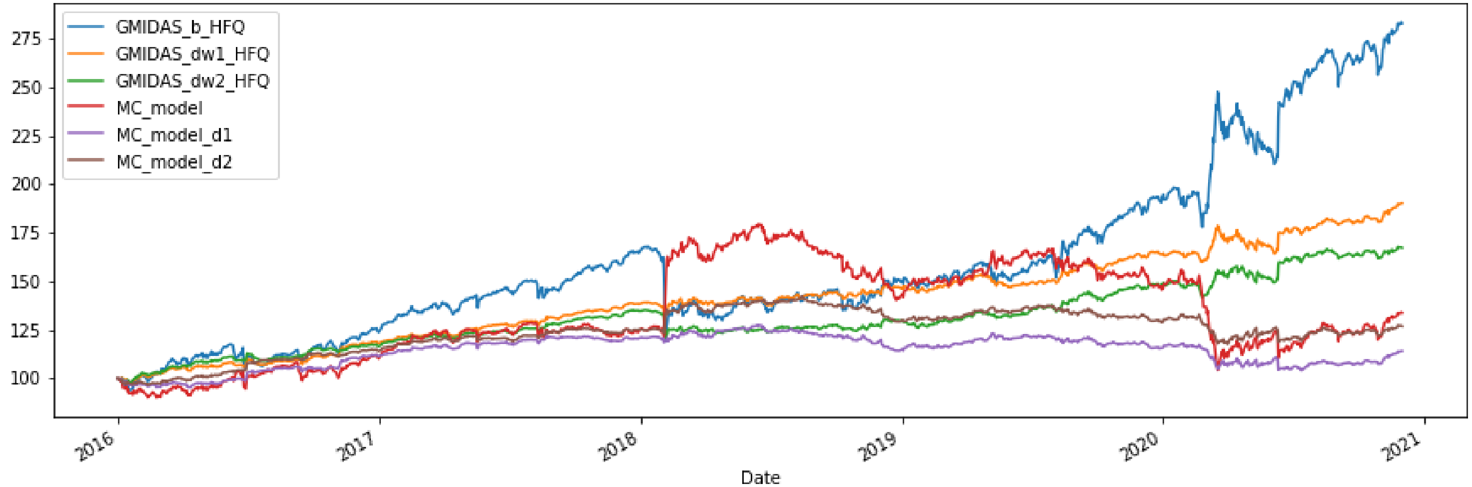
- Binary
- Scaled (RSI)

- Rebalanced daily at close
- 75% are always in cash

# Results

## Methodology

### Equity Curve Out of sample




### Performance Measures Out of sample

| | GMIDAS_B | GMIDAS_RSI_1 | GMIDAS_RSI_2 | MC_B | MC_RSI_1 | MC_RSI_2 |
|---|---|---|---|---|---|---|
| CAGR | 23.51% | 13.99% | 11.16% | 6.10% | 2.73% | 4.97% |
| Sharpe ratio | 1.11 | 1.68 | 1.31 | 0.38 | 0.38 | 0.62 |
| Sortino ratio | 1.53 | 2.9 | 1.94 | 0.62 | 0.54 | 0.97 |
| Max. drawdown | -29.11% | -8.14% | -10.68% | -41.87% | -18.29% | -17.45% |
| Calmar ratio | 0.81 | 1.72 | 1.04 | 0.15 | 0.15 | 0.28 |