Machine Learning for Volatility Trading

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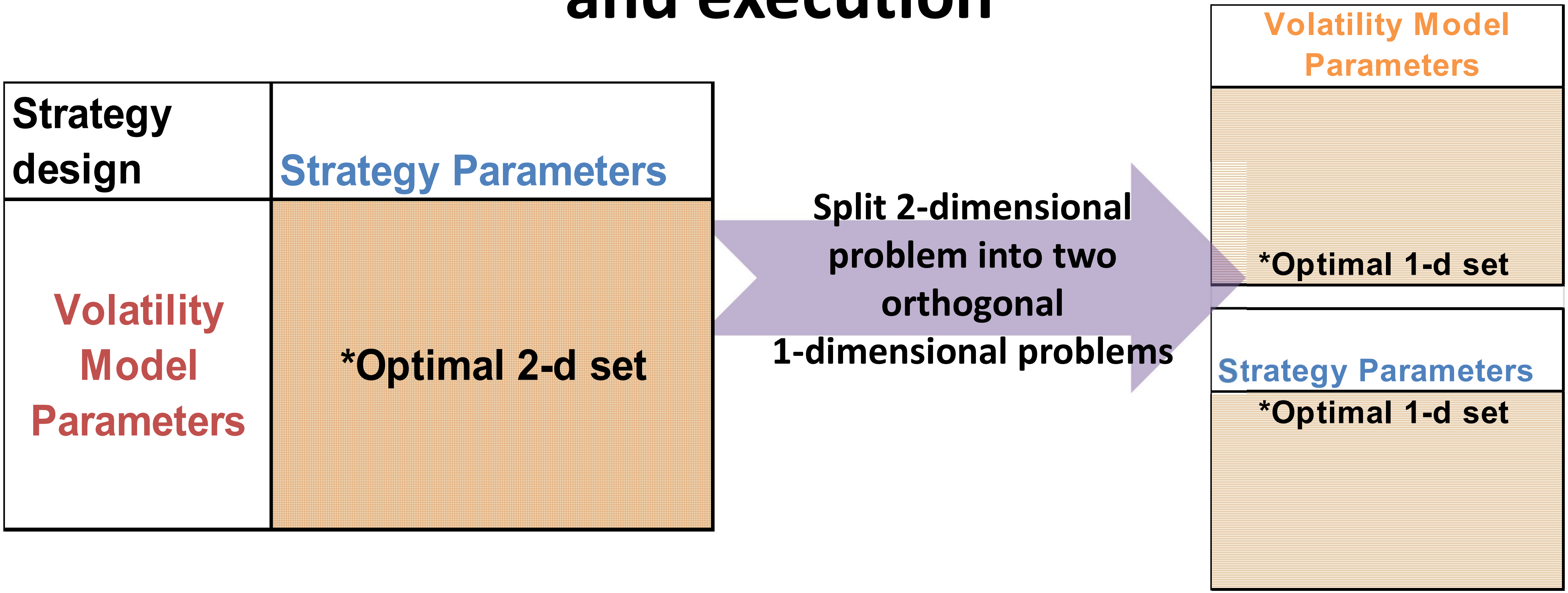
Machine Learning for Volatility Trading

- Link between realized volatility and P&L of quant strategies trading volatility
- Supervised learning & learning to rank for selecting best models for volatility forecast
- Supervised learning for stock volatility forecast at earnings releases
- Machine learning for risk management of aggregated option books

Machine Learning is applied to forecast volatility and risk metrics

	Volatility Trading (Systematic)	Risk Management of Volatility Books (Flow and Systematic)	Risk-Premia & Factor-Based Investing
Why?	Niche strategies for the buy side	Most of risk is managed using traders' heuristics	Recognition and demand from institutional investors
How?	Learn to select top models with best forecast power	Learn optimal risk-hedging process from market data	Learn to identify risk-profile and best regimes for strategy performance

Machine learning for volatility estimation reduces the dimensionality of strategy back-test and execution



Machine Learning and Bayesian approach are applied for strategy design

Volatility model

= The hyperparameter of returns distribution learned by ML methods from data

Bayesian prediction of returns

= Distribution of observed data conditional on the volatility model

* Distribution of the hyperparameter

Strategy Parameters

= Estimated and executed on the Bayesian prediction of returns and volatilities

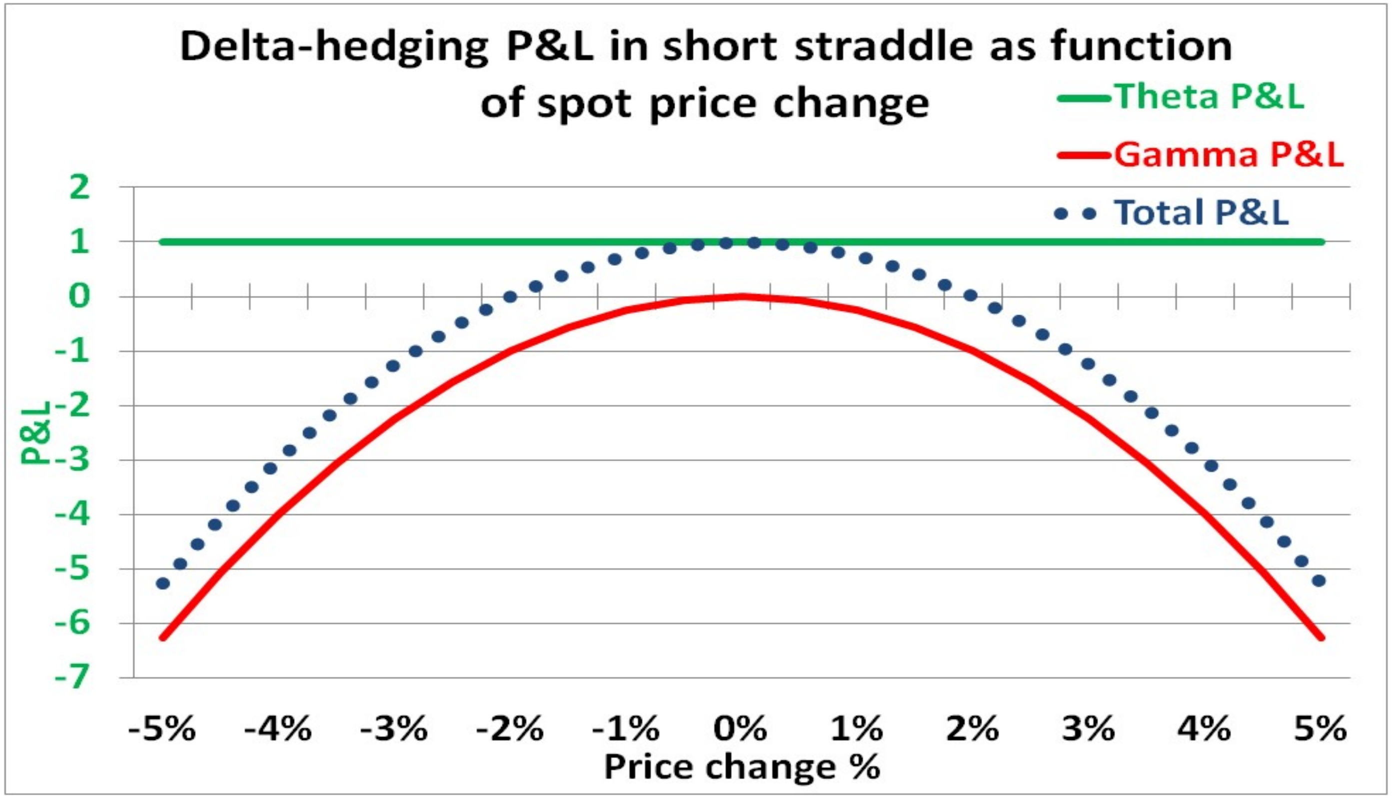
Optimal volatility model is applied to trading strategies

- **Volatility trading:**
  Prediction of expected realized volatility
- **Trend-following:**
  Normalization of time series to uniform standard deviation
  Detection of autocorrelation
- **Asset allocation/portfolio construction:**
  Normalization for estimation of covariance matrix

Option payoffs can be replicated by the dynamic delta hedging

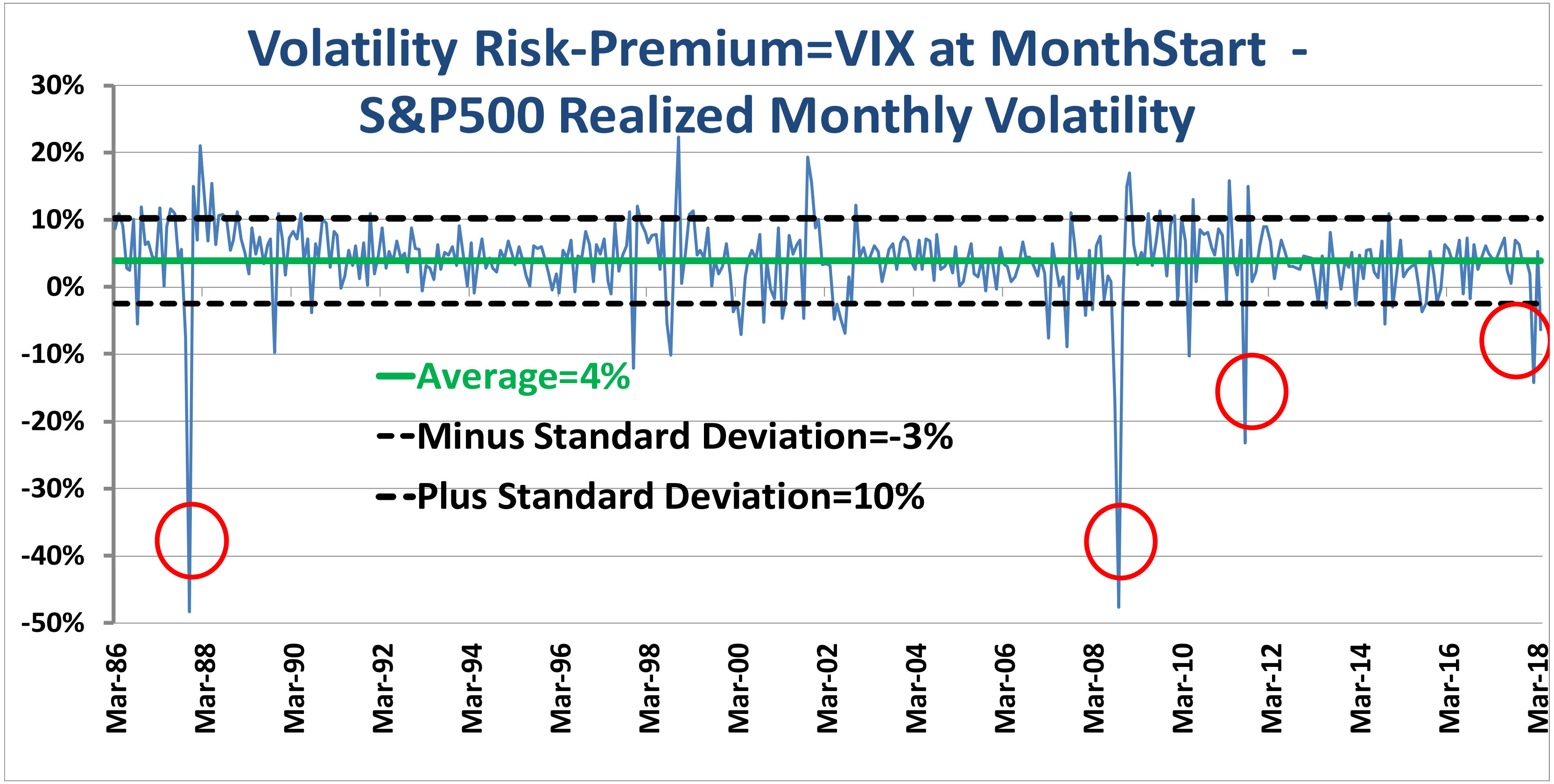
- **One-Step Delta-hedged P&L for short straddle**

  = Option Time Decay (Theta P&L) - Realized Convexity (Gamma P&L)



Forecast of realized volatility is applied to estimate volatility risk-premium

- **Relative value trading**: sell/buy options with high/low expected spread & delta-hedge
- **Signal filtering:** forecast drawdowns (deal with high non-linearity and back-test overfit)



Volatility forecast is applied for the statistical estimation of the option value (vs market price)

- Each risk factor is estimated using volatility forecast and assigned risk-premia

Option Value (Expected Replication Costs)=

- + Replication Costs (Realized Gamma) = Realized Volatility * Gamma
- + Transaction Costs (For delta trading)=|Realized Gamma| * Bid/Ask Costs
- + Gap Risk (Un-hedgable delta-risk)=Price Crashes & Illiquidity
- + MTM Valuation Risk (Vega risk) = Changes in implied volatility

Multiple classes of volatility models are applied for the forecast of realized volatility

Sample space estimators

- Close-to-close, Intraday estimators (Parkinson, etc…)
- Assume random walk for the volatility

GARCH models

- Garch (1,1), Asymmetric Garch, etc
- Apply long-term history with mean-reversion

Bayesian parametric models

- Continuous type models with priors for vol forecast
- Apply intraday high/low price data

Hidden Markov Chain Models (HMC)

- Discrete states of volatility
- Classification problem in unsupervised machine learning

The predicative power of volatility models is assessed using specifically designed tests

- **Cannot use P&L from strategies to avoid over fit:**

  1. Delta-hedged option P&L is highly path-dependent and cyclical

  2. Volatility forecast impacts the hedging policy (in contrast to linear buys/sell predictions)

  3. Options strategies have multiple dimensions: strike, maturity, hedging policy

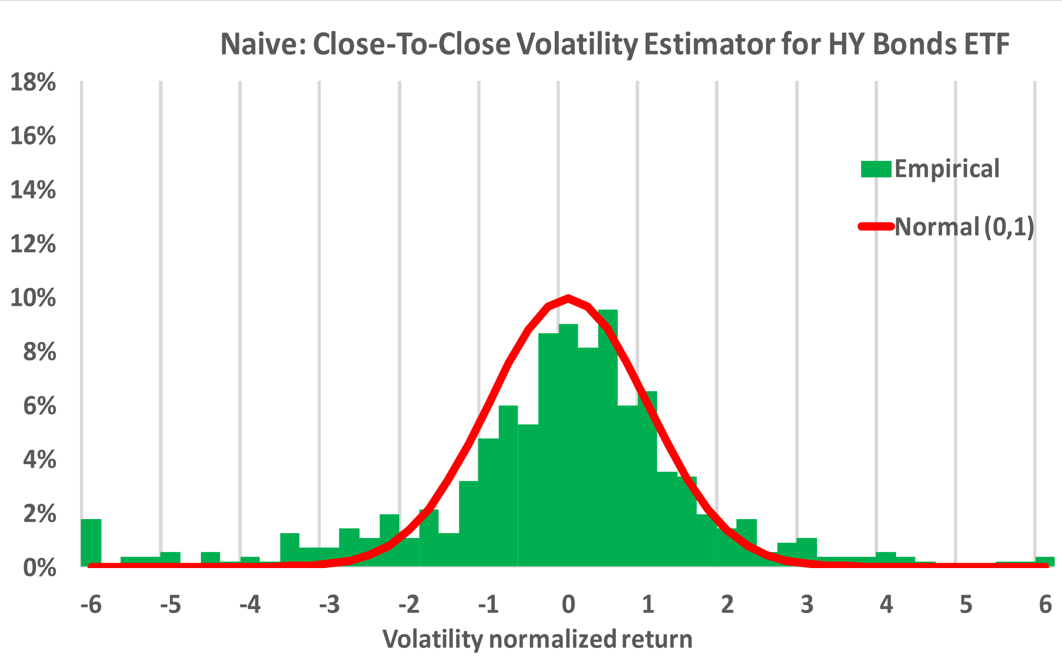
- **Instead, compare model forecast to benchmark tests, for example:**

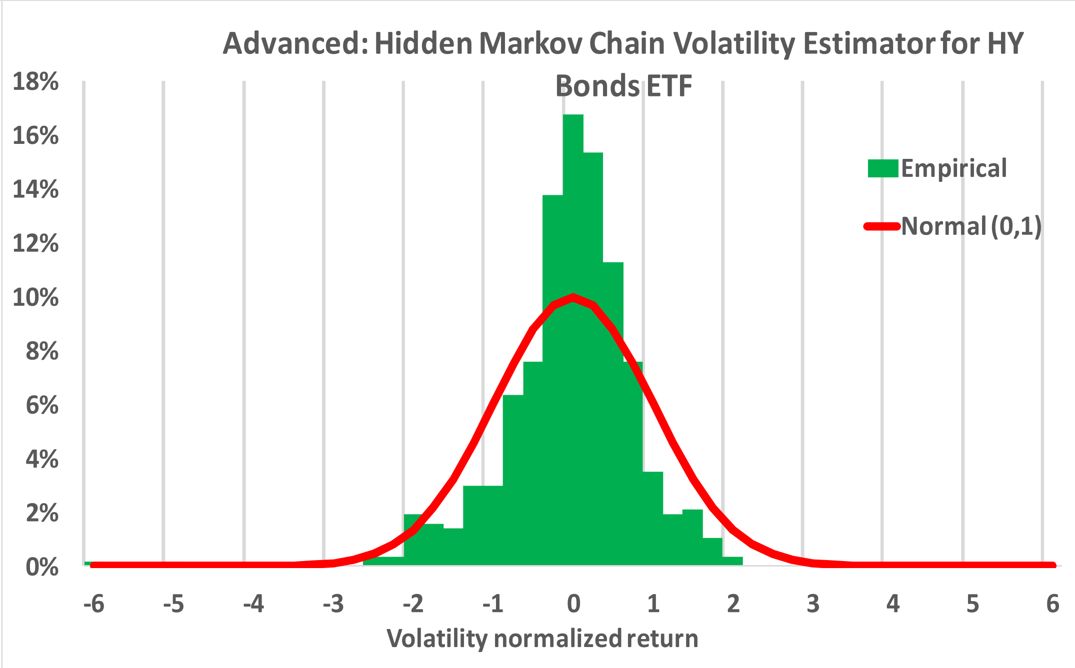
  1. Benchmark to close-to-close volatility for end of day hedging
  2. Distribution tests for the stability of the forecast

Distribution tests is applied for volatility normalized returns over forecast period

$$Z(n) = \frac{Realized\ Return\ (n)}{Volatility\ Vorecast(n)}$$

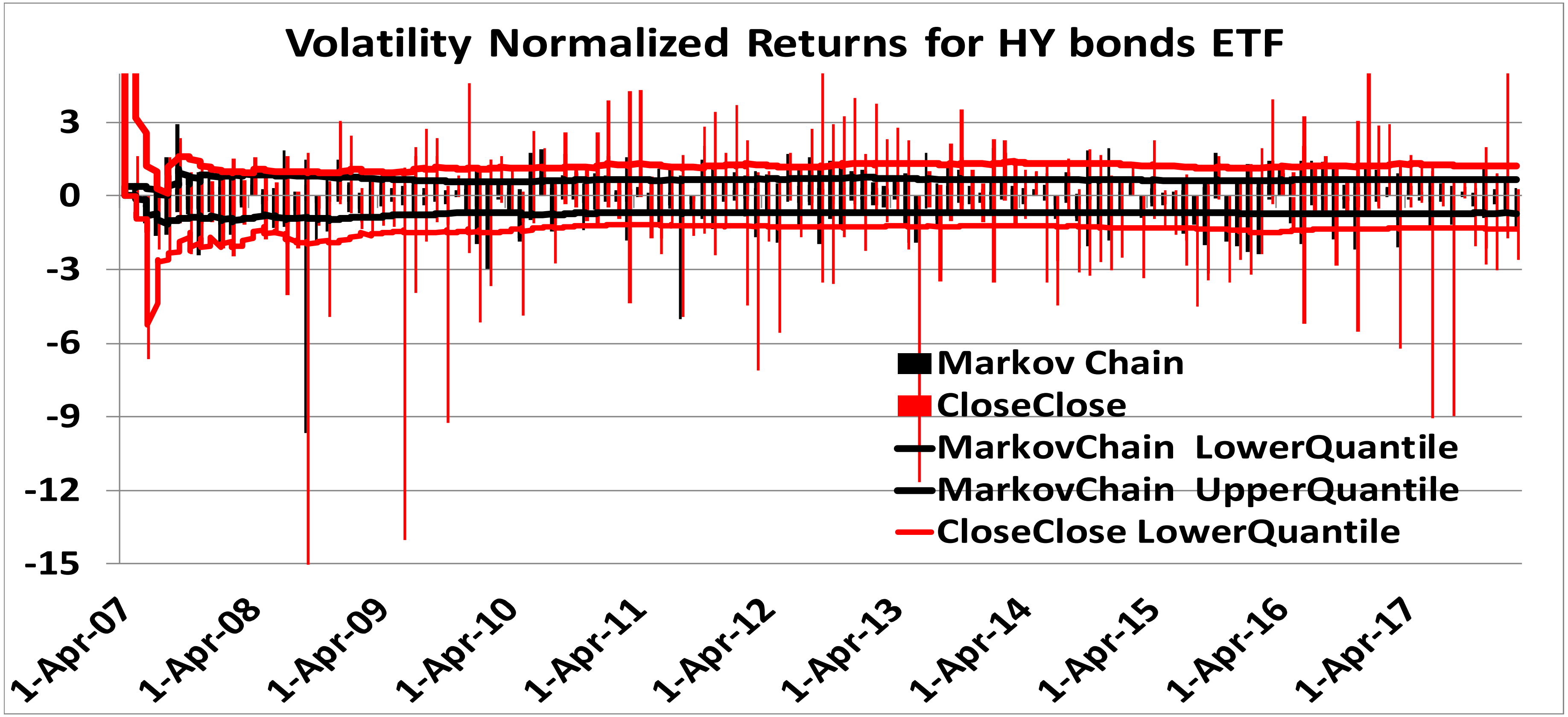
For a model with strong predicative power, sample distribution of Z(n) is symmetric with standard deviation of 1 (unbiased forecast)





Robust estimator provides tight bounds for volatility forecast with no "surprises"

- Robust application for strategies with volatility targeting and time series normalization

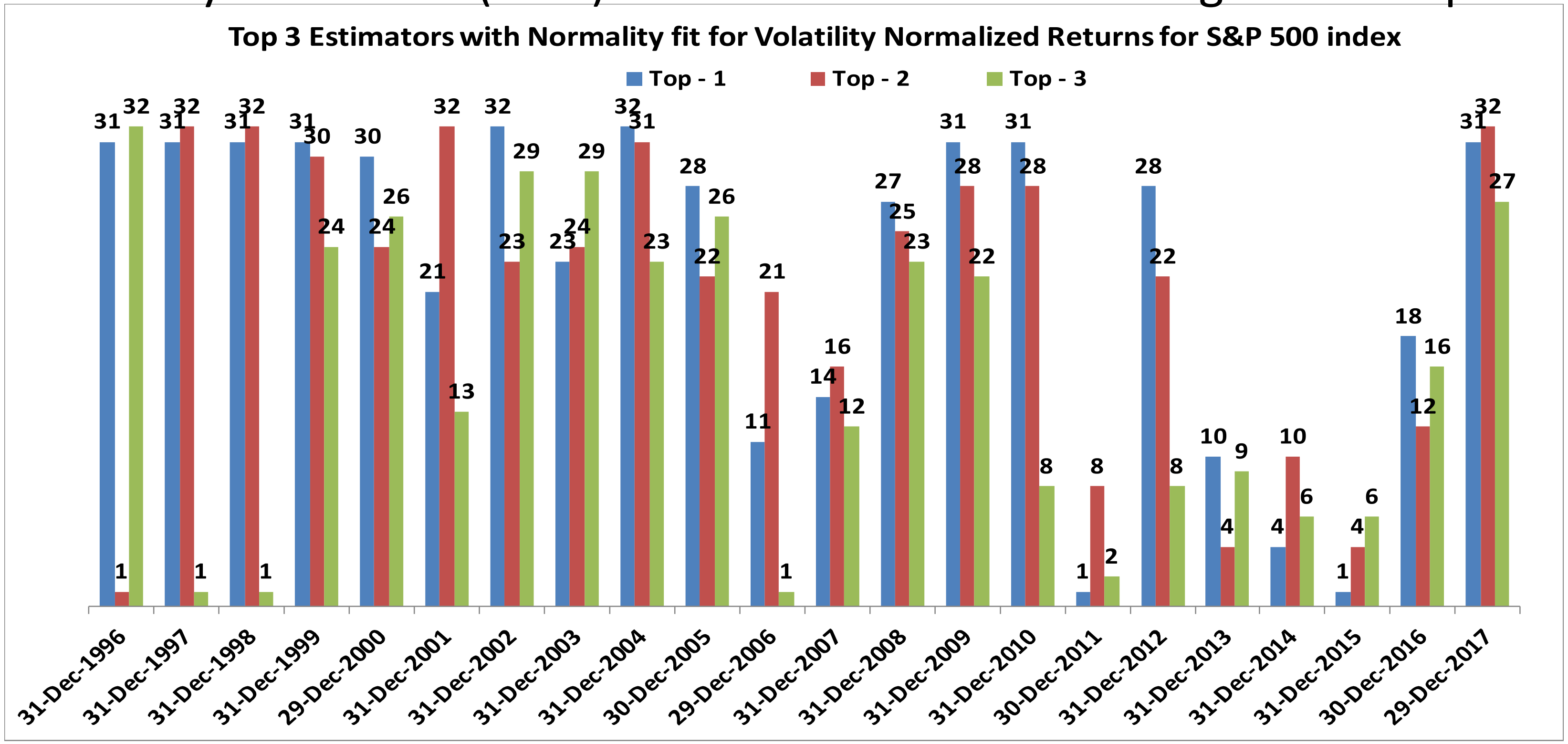


Supervised Machine Learning is applied to Rank Models

Model implementation	N (>30) different volatility models for forecasting
Test Design	M (>=1) statistical tests to assessing the power of the model forecast
Performance Evaluation	The performance is evaluated regularly (annually, quarterly, monthly, etc)
Ranking	M ranks based on the statistical power of the tests at each performance evaluation
Selection	Selection of the top model or a combination of top models
Learning to rank	Forecasting of the top model at next performance evaluation (learning to rank)

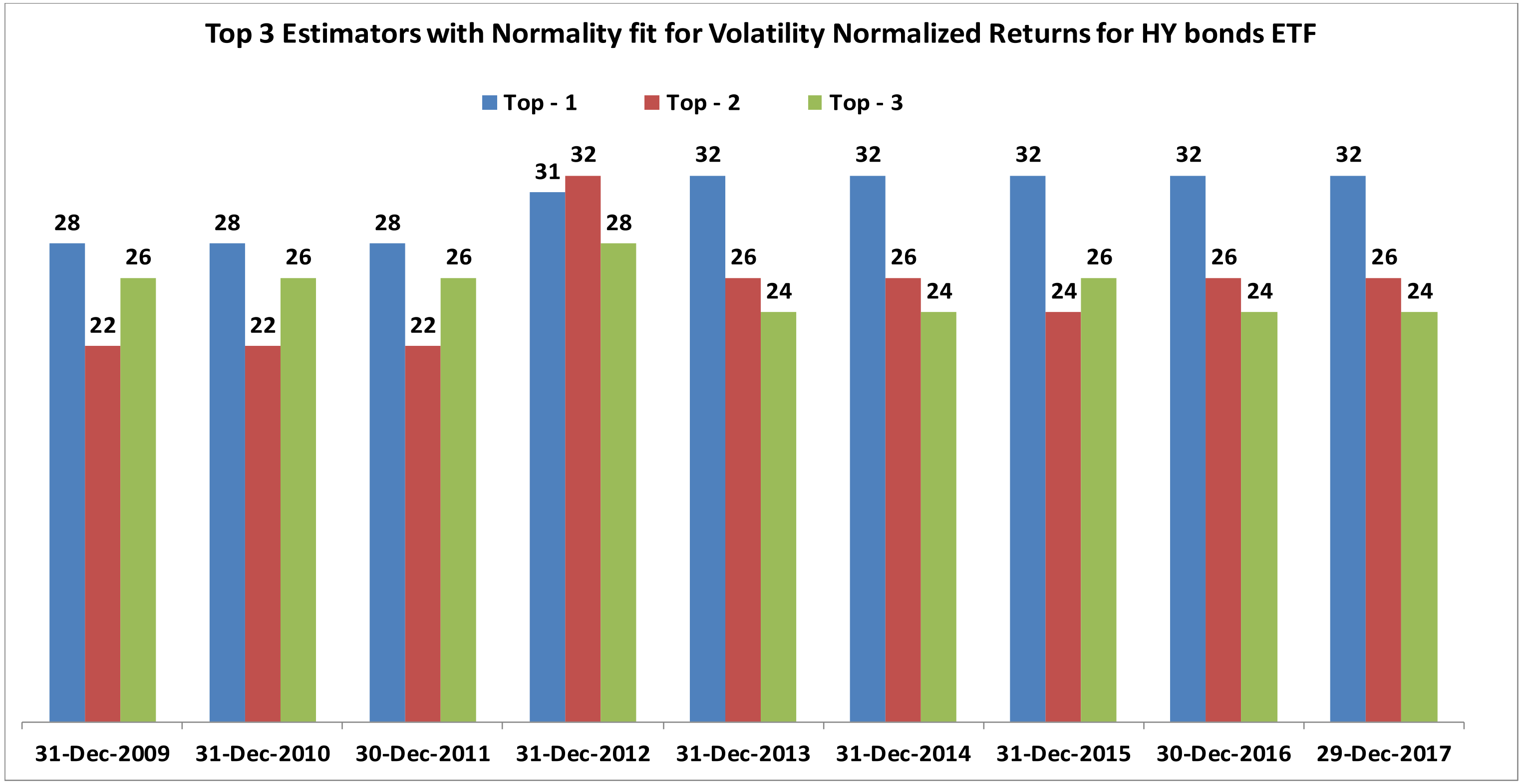
Top-3 models for the S&P 500 index using normality test in walk-forward analysis annually

- Use past rolling window of 3 year for one step forecast evaluation
- Each model is numbered (1,2,…)
- Markov Chain models (31,32) are frequently on the top
- Intraday estimators (1-10) are also reliable while being least complex



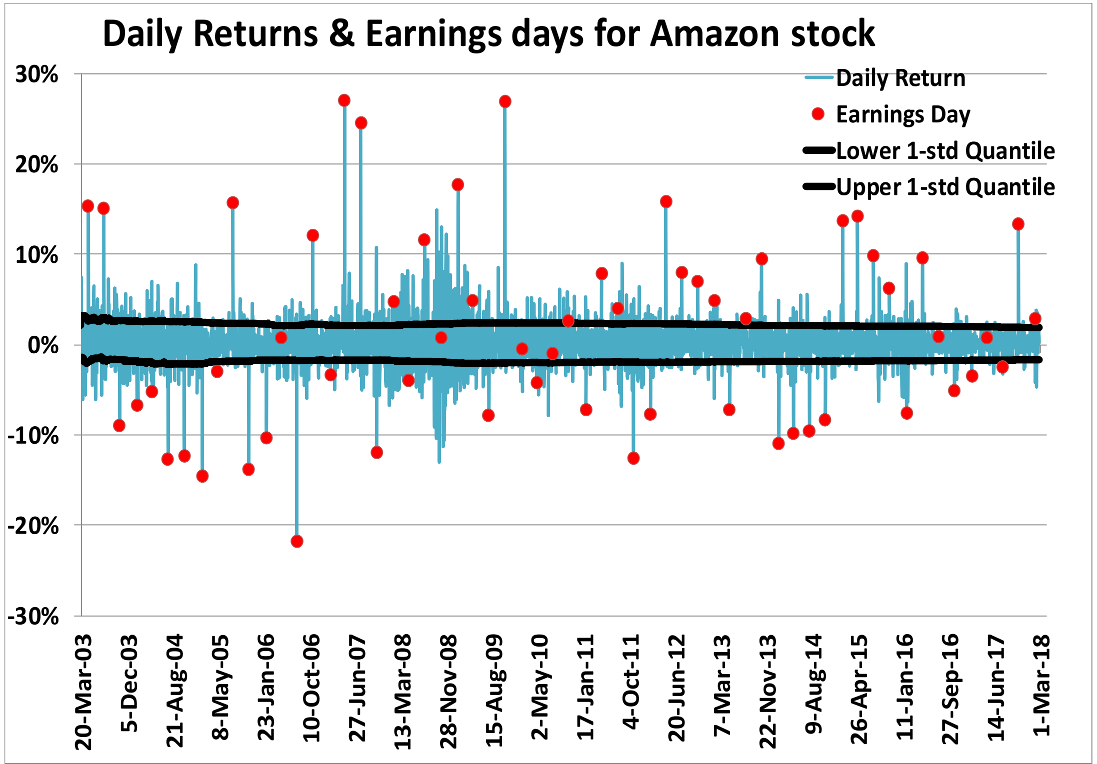
Top-3 models for High Yield Bonds ETF using the normality test annually

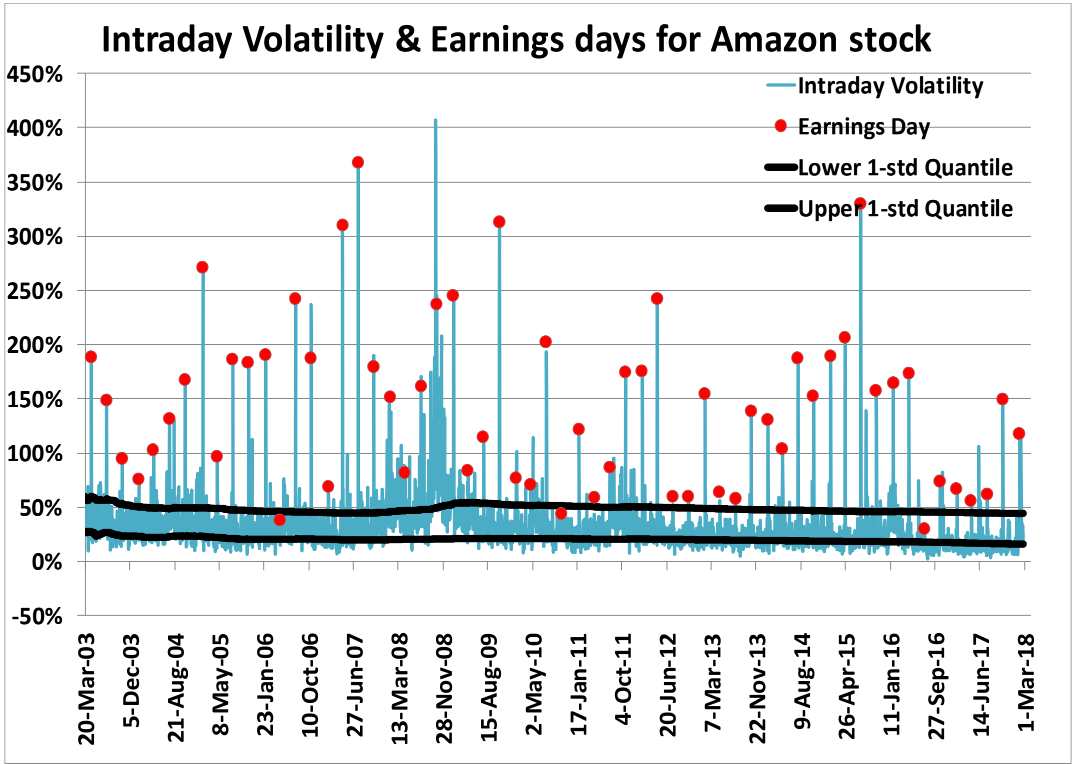
- Stable ranks for Markov chain (31-32) and GARCH models (21-30)



Stock daily returns and intraday volatility are extreme on earnings release days

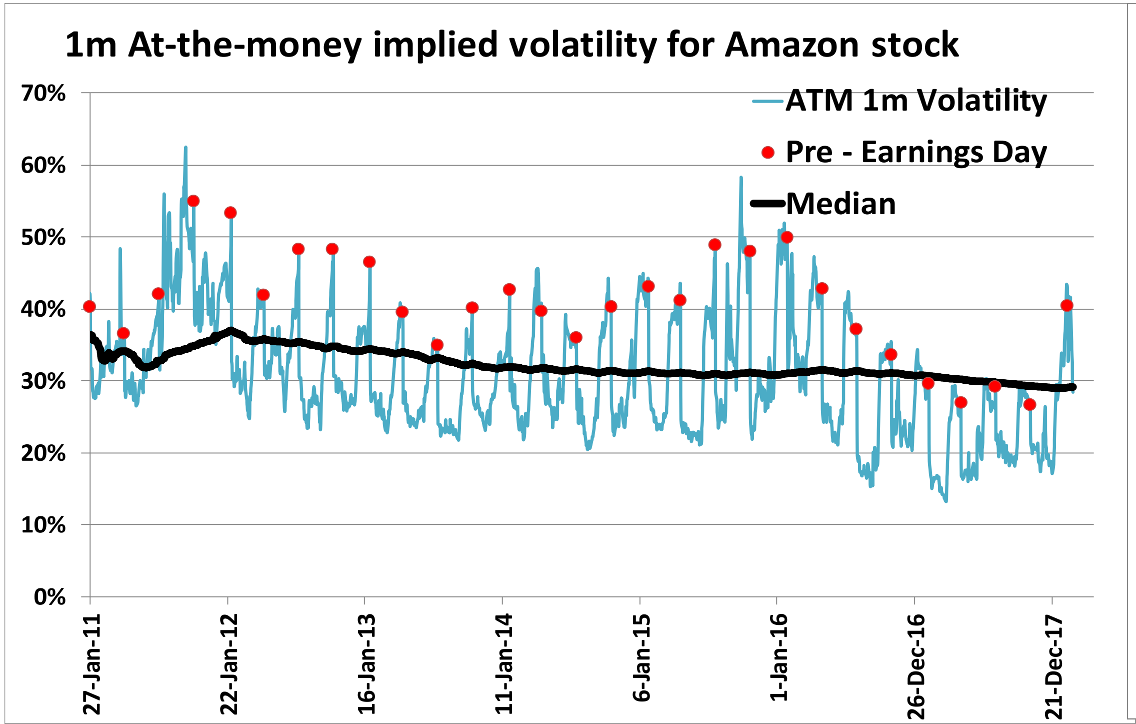
- Learn to adjust and forecast volatilities around special days

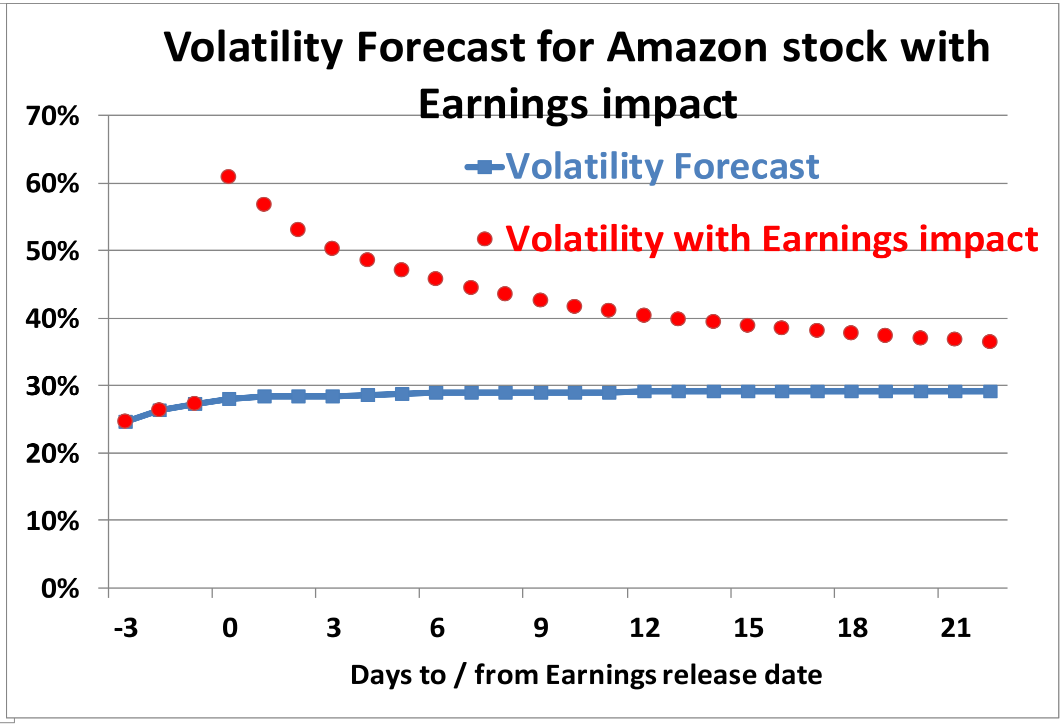




High weights are assigned for volatility forecast over earnings release days with applications to relative value trading

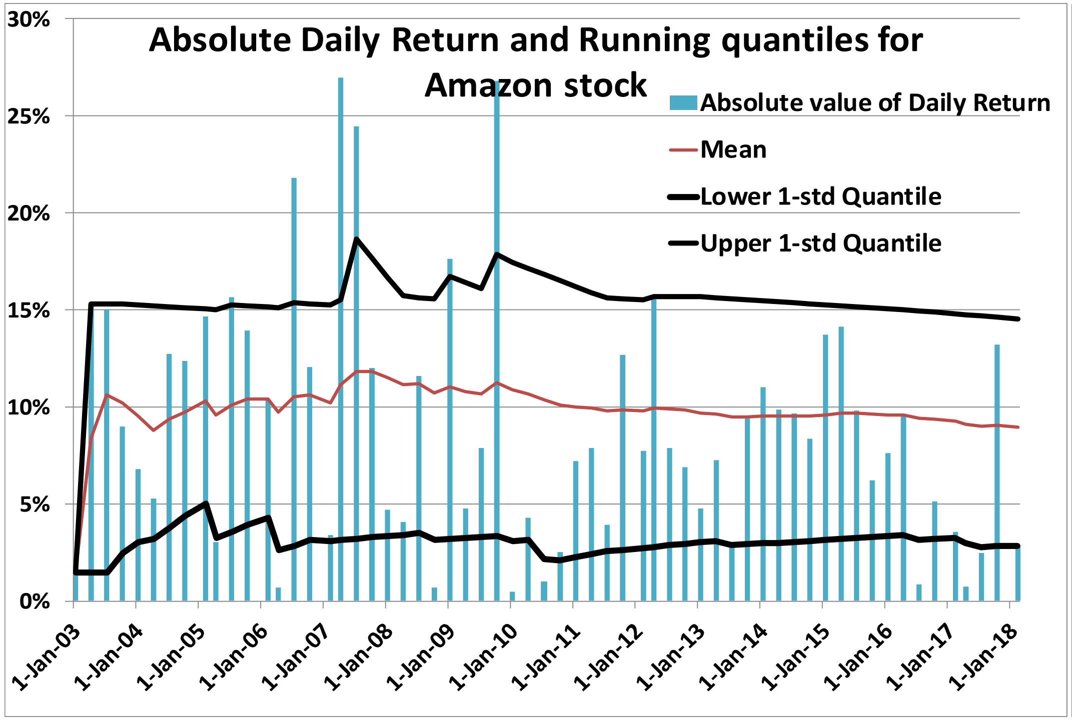
- Implied weights can be inferred from the term structure of ATM implied volatility
- Realized/forecasted weights can be learned from historical data

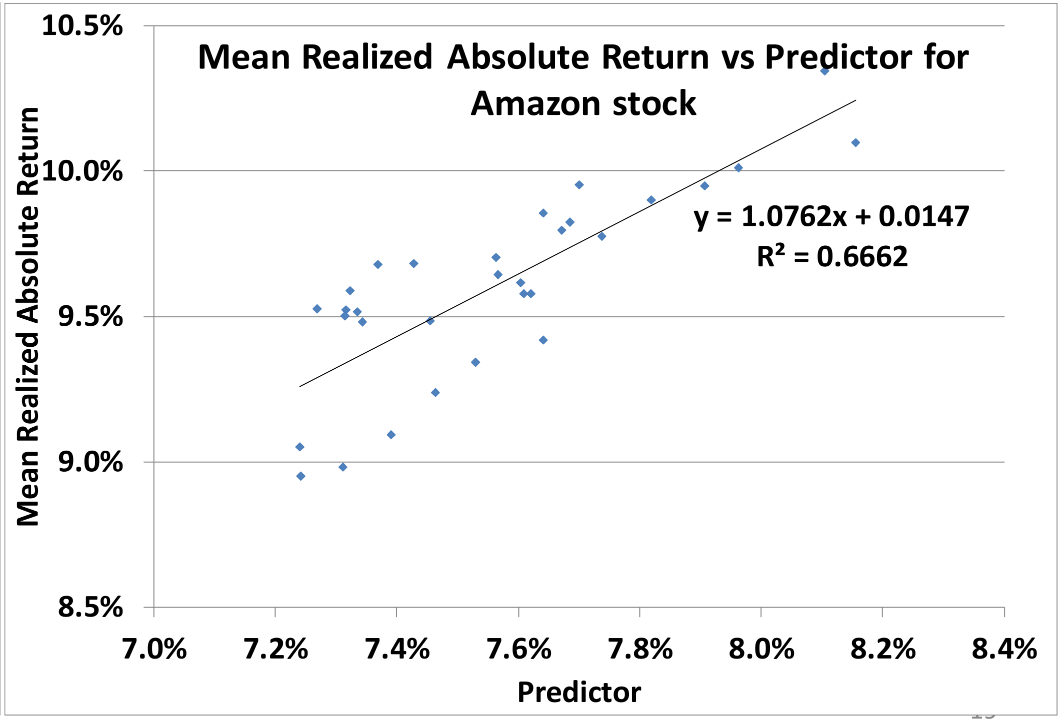




Machine learning using intraday estimators is applied for volatility forecast over special days

Expected absolute value of return on earnings day
= Scaling * Estimated Intraday volatility





Machine learning for selection of the best volatility model is applied on asset class level

Aggregation by Asset Class:

1. Stock Indices
2. Technology Stocks
3. Agricultural Futures
4. G-10 FX
5. …

Learning phase for tests 1, 2,… walk-forward with regular evaluations:

1. Stock Indices:
   Rank1 (t1), Rank1(t2),…
   Rank2(t1), Rank2(t2),…
   RankM(t1), RankM(t2),
2. …

Query processing:

- Volatility forecast for the S&P 500 index on 14-May-2018 for next month for delta-hedged volatility carry
- …

Machine learning enables robust management of portfolio of live and back-tested strategies

Smaller likelihood of back-test overfit:

- When a trading algo requires volatility forecast at time t, it is provided with the best forecast known at t

Test for forecast evaluation are tuned to algo types:

- Signal for volatility carry delta-hedged: test for best prediction of intraday volatility
- Volatility-target allocation with monthly rebalancing: test for the normality of volatility-normalized returns

Dynamic selection of volatility forecast for live strategies:

- Robust adaptation to regime-changes

Processing queries with learning to rank is analogous to web search engines

Query:

Fetch volatility forecast for the S&P 500 index on 14-May-2018 for next month for delta-hedged volatility carry

Search engine:

1. Analyse the collection of available tests results and ranks
2. Output forecast from single model or a linear combination of models

Evaluation of "user" satisfaction:

1. Use P&L realized by the querier strategy
2. Tune up the weight of tests for different queries (delta-hedged volatility carry vs volatility-target allocation)

Application to Business model in Option Trading

Trade generation using systematic strategies with Machine Learning

Identify exchange-traded options with the highest expected reward-to-risk ratio

Trade generation from flow/exotic business

Look for OTC options with highest commissions/margins

Option Book

1. Positions & Hedges
2. P&L Report
3. Aggregated Risk Report

Statistical risk model with ML

1. Model-defined risk (delta,vega,…
2. Risk Aggregation on Book level
3. Stress testing on book level

Valuation model for Risk

Aggregated Risk Report with mark-to-market valuation adjustments using historical data

Mark-to-Market Valuation Model

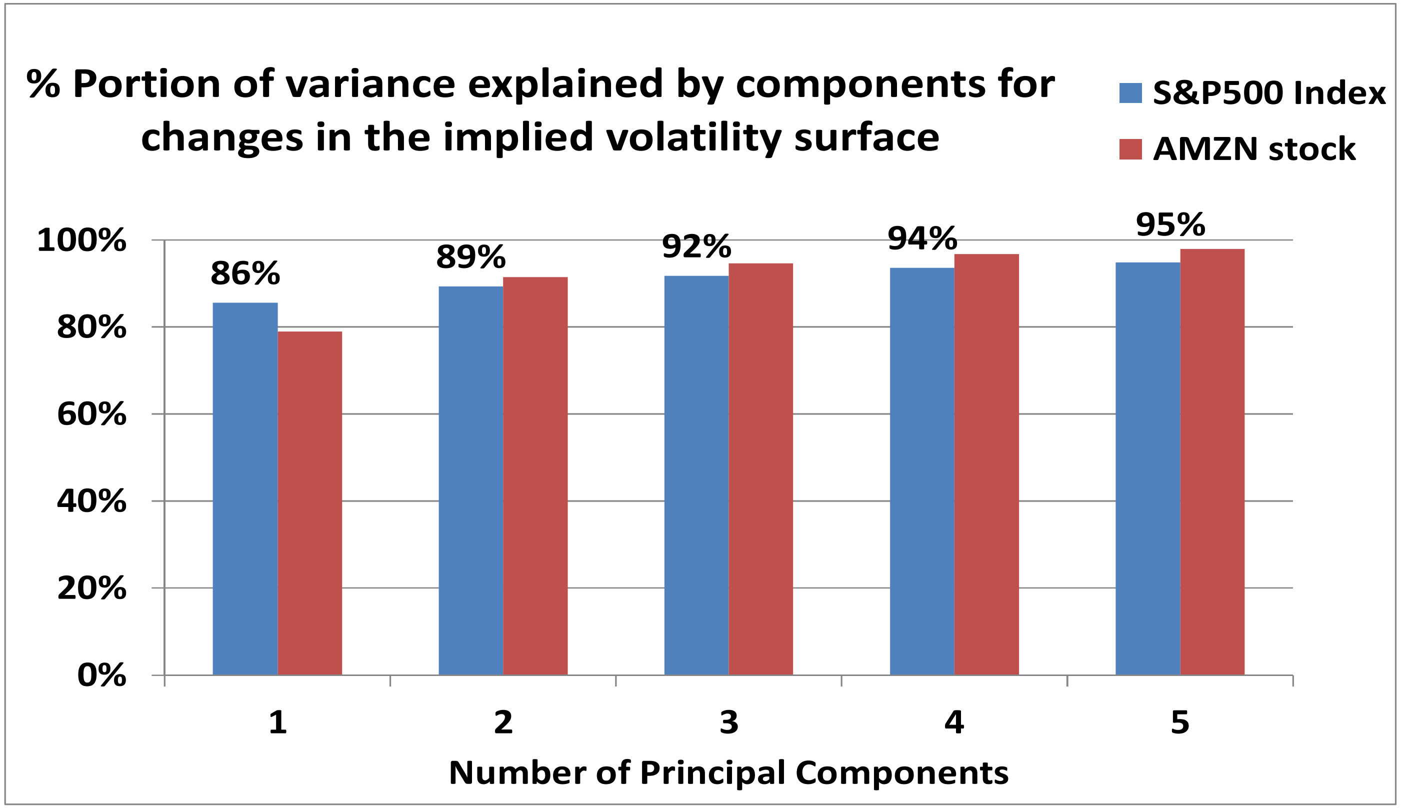
1. P&L Report
2. Margin Report

Machine Learning can be applied for Automated Risk Management of Option Books

	Delta risk	Vega risk	Gamma / Tail risk
Driver:	Change in the asset price	Change in the implied volatility	Second and large order changes
Learn:	- Scaling of delta for different assets - Aggregation on the index level	- Vega aggregation at maturities/strikes - How delta impacts vega risk	-Scenario/stress test analysis - Regime conditional risk

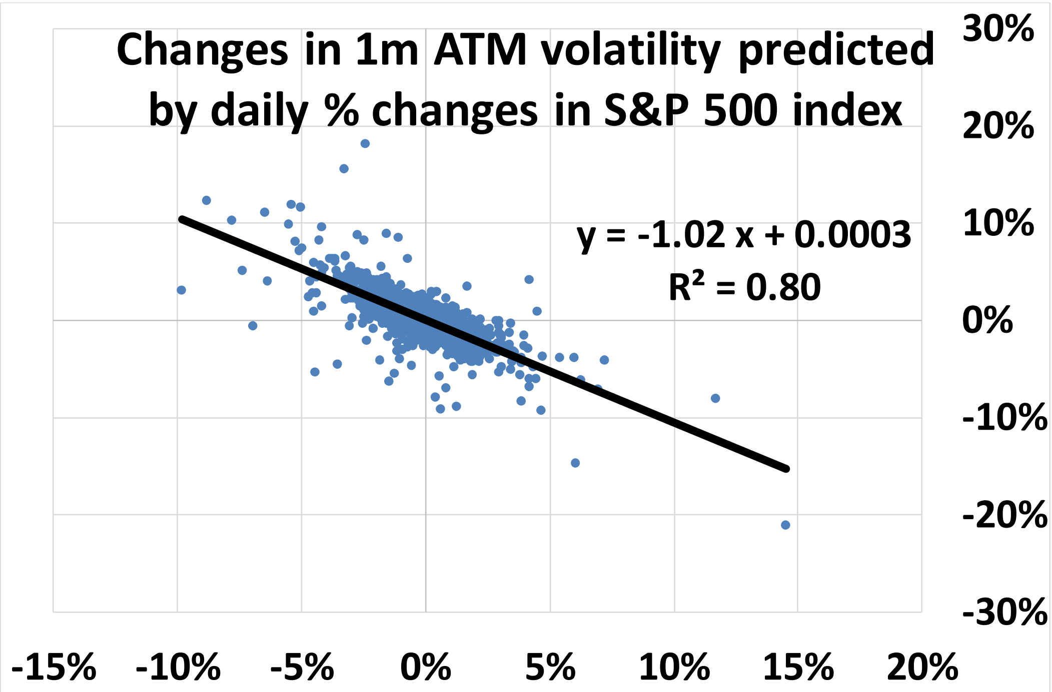
Low number of statistical risk factors (2-3) explain vega and delta risk

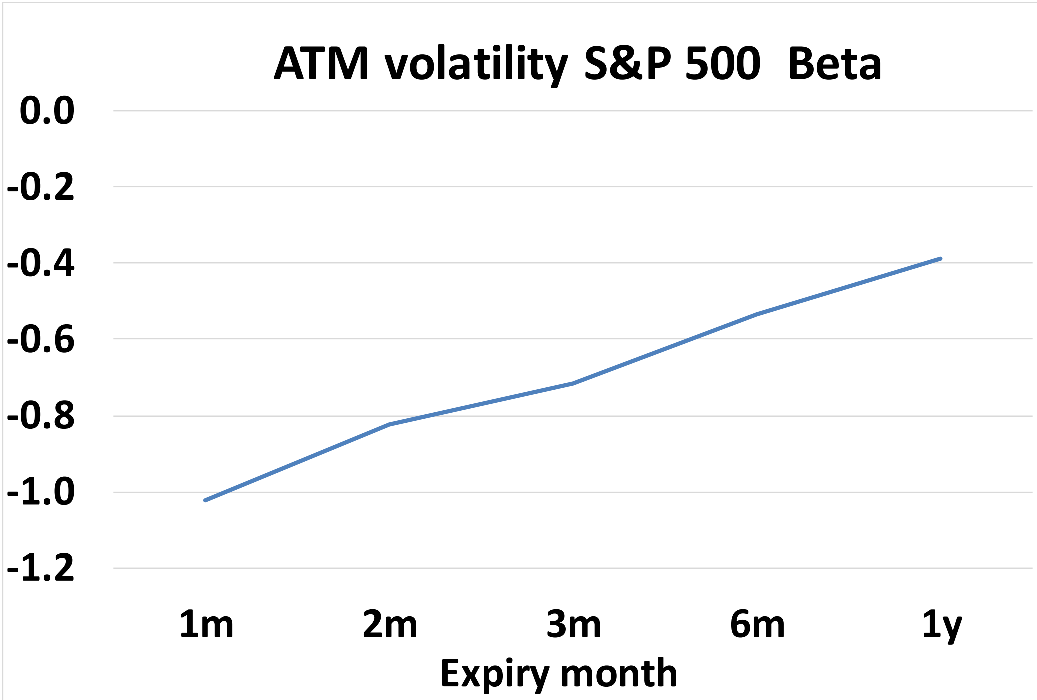
- Apply PCA on changes in price and implied volatility surface



Delta to Vega risk mapping using regression

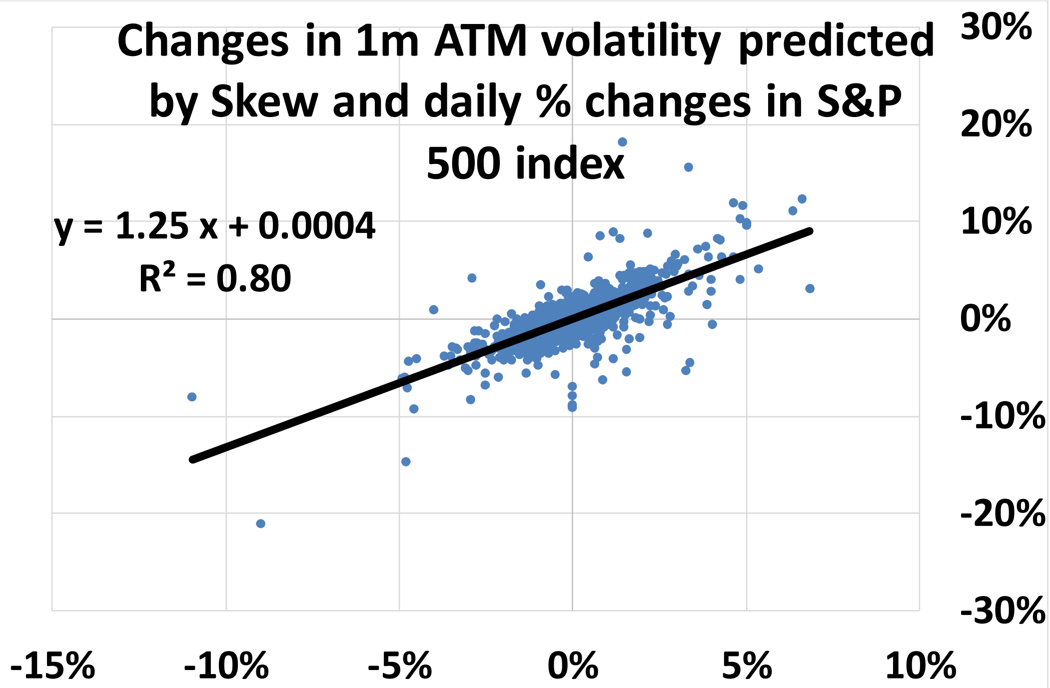
- Learn how changes in volatility are influenced by changes in the underlying asset
- Strong negative beta for short dated options

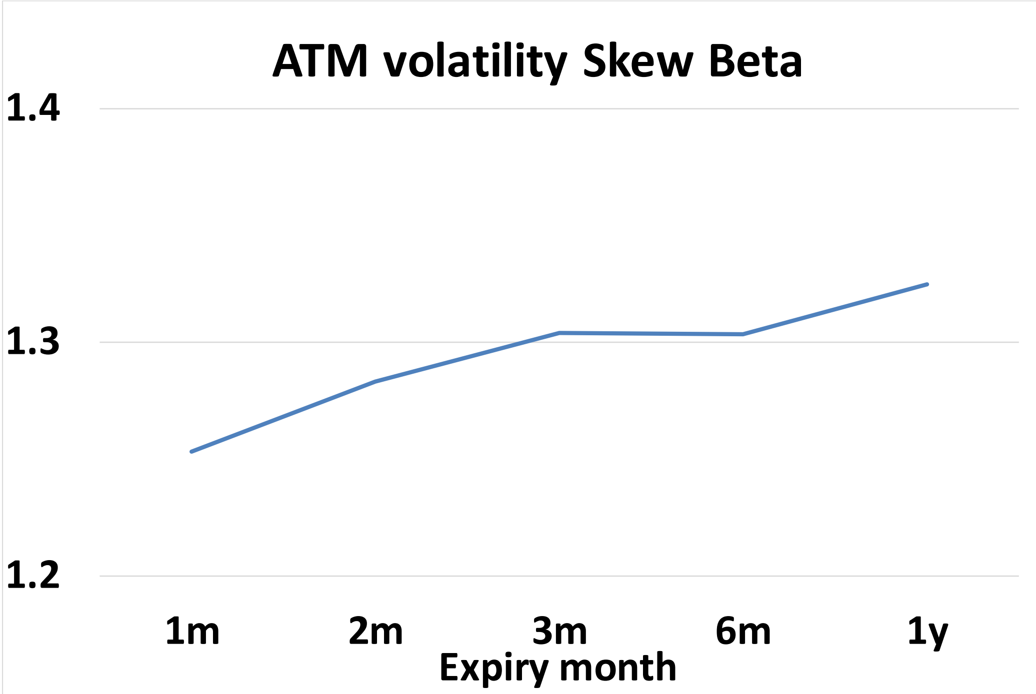




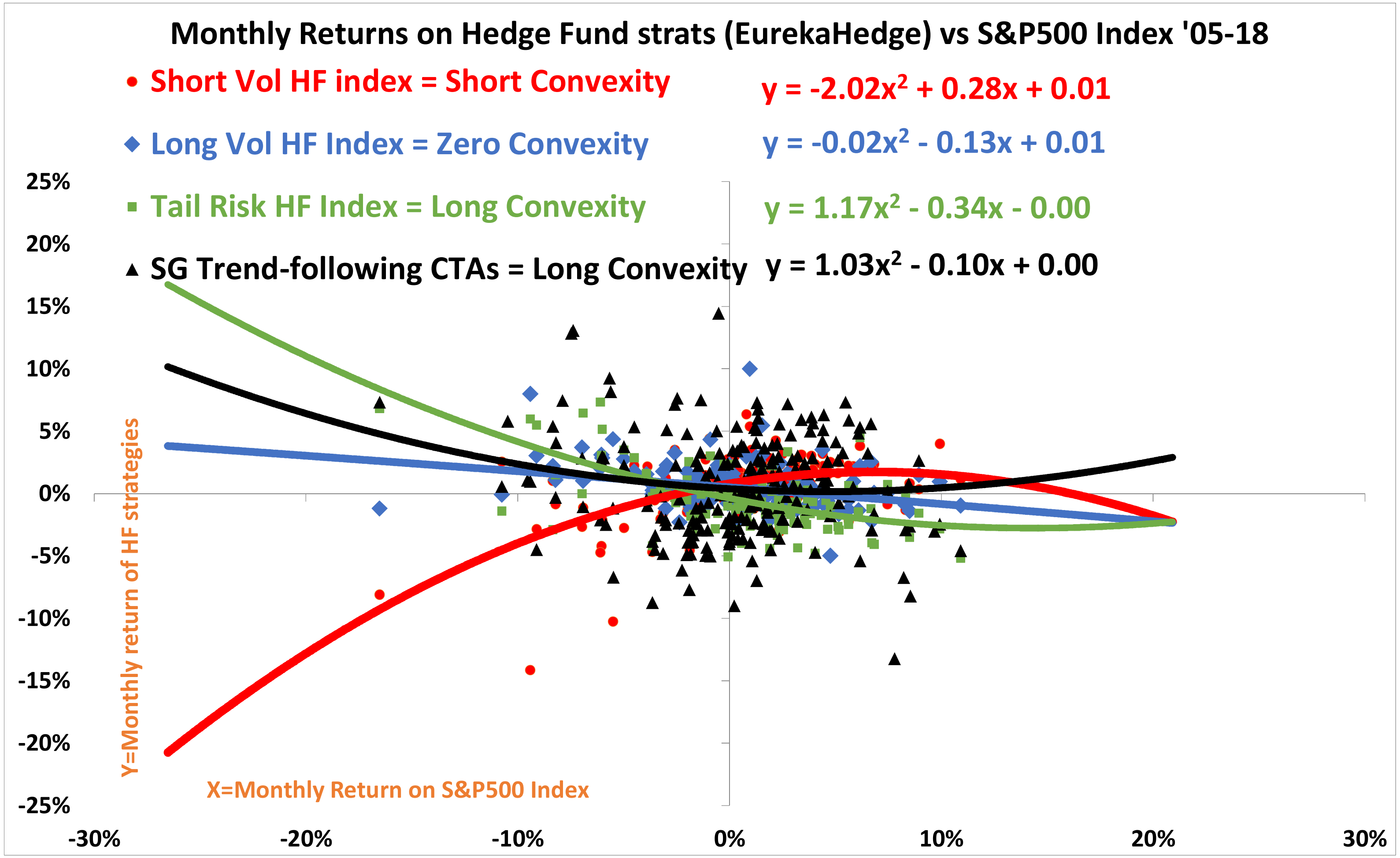
Adjustment of Delta for Vega risk using regression

- Market-based prediction for Vega risk from delta = Skew * Price Change
- Volatility skew beta is applied to hedge for the contribution to vega risk from the delta



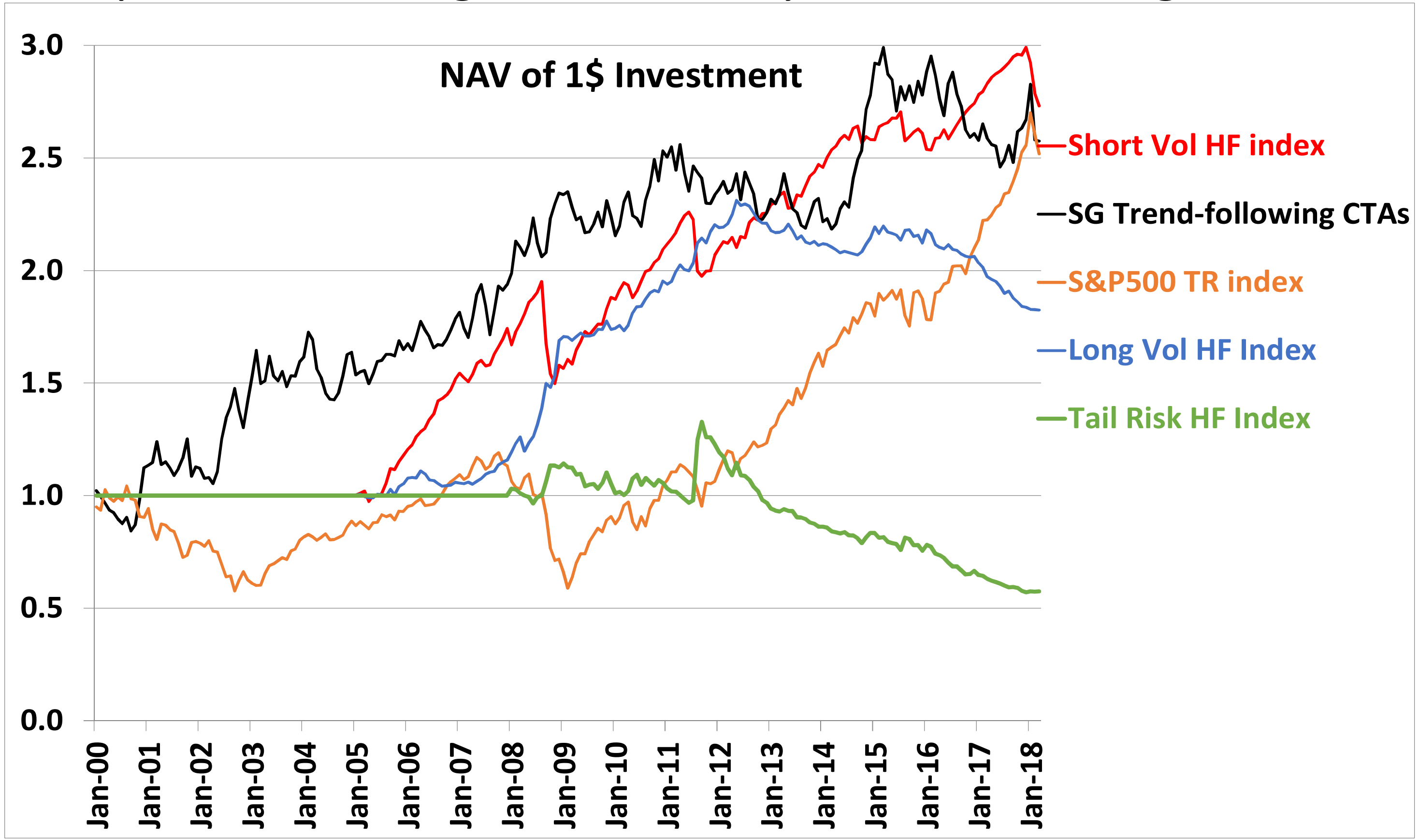


Big Picture Investing: Learning the convexity profile of quant investment strategies



Learning regimes of outperformance can be applied for portfolio allocator of quant strategies

- Top-down allocator using regime-based inference
- Bottom-up allocator using scenario analysis and clustering



Conclusions: Volatility model estimation with Machine learning is adapted to financial data

Data are scare

- Aggregate model estimation across multiple instruments and assets

Dynamics are different at different time scales

- Different models for different scales (daily, weekly, monthly) dependent on average rebalancing of a strategy

Dynamics are non-stationary

- Performance of forecasting models is evaluated regularly and the model choice is adaptive

Occam's razor and Minimum description length

- Select the answer that makes the fewest assumptions
- Look for a model that best predicts the data, out of several hypotheses
- Layered/conditional models have less sensitivity to error propagation

Kolmogorov complexity and mutual information:

the shortest program to produce BOTH Data AND Model

= program to produce model

+ program to produce data given model

Leading terms

+ logarithmic term

Second order corrective term

Conclusions: Machine Learning for volatility trading

Machine learning for volatility model selection

- Apply a large number of models for vol prediction
- Rank models using specified tests
- Aggregate ranking on the level of asset classes

Query processing

- Select the best model or their combination for the customised response to the query

Applications for quant algo trading and asset allocation

- Query for the volatility forecast
- Apply the volatility forecast for strategy execution
- Refine queries based on feedback from strategy

References to Personal work

1. **When You Hedge Discretely: Optimization of Sharpe Ratio for Delta-Hedging Strategy under Discrete Hedging and Transaction Costs** http://ssrn.com/abstract=1865998
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5. **Trend-Following Strategies for Tail-Risk Hedging and Alpha Generation** https://ssrn.com/abstract=3167787

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