Applications of machine learning for volatility estimation and quantitative strategies

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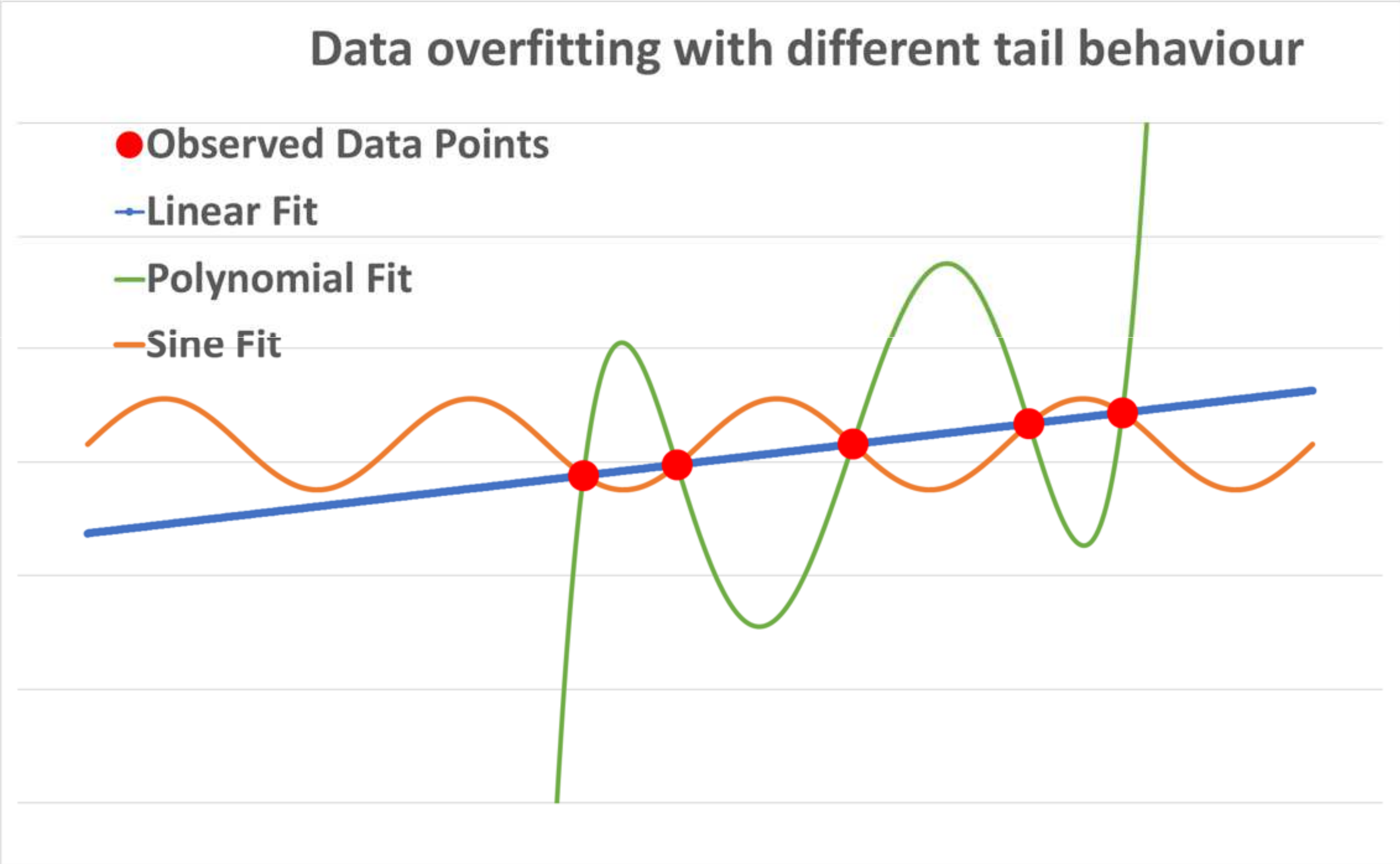
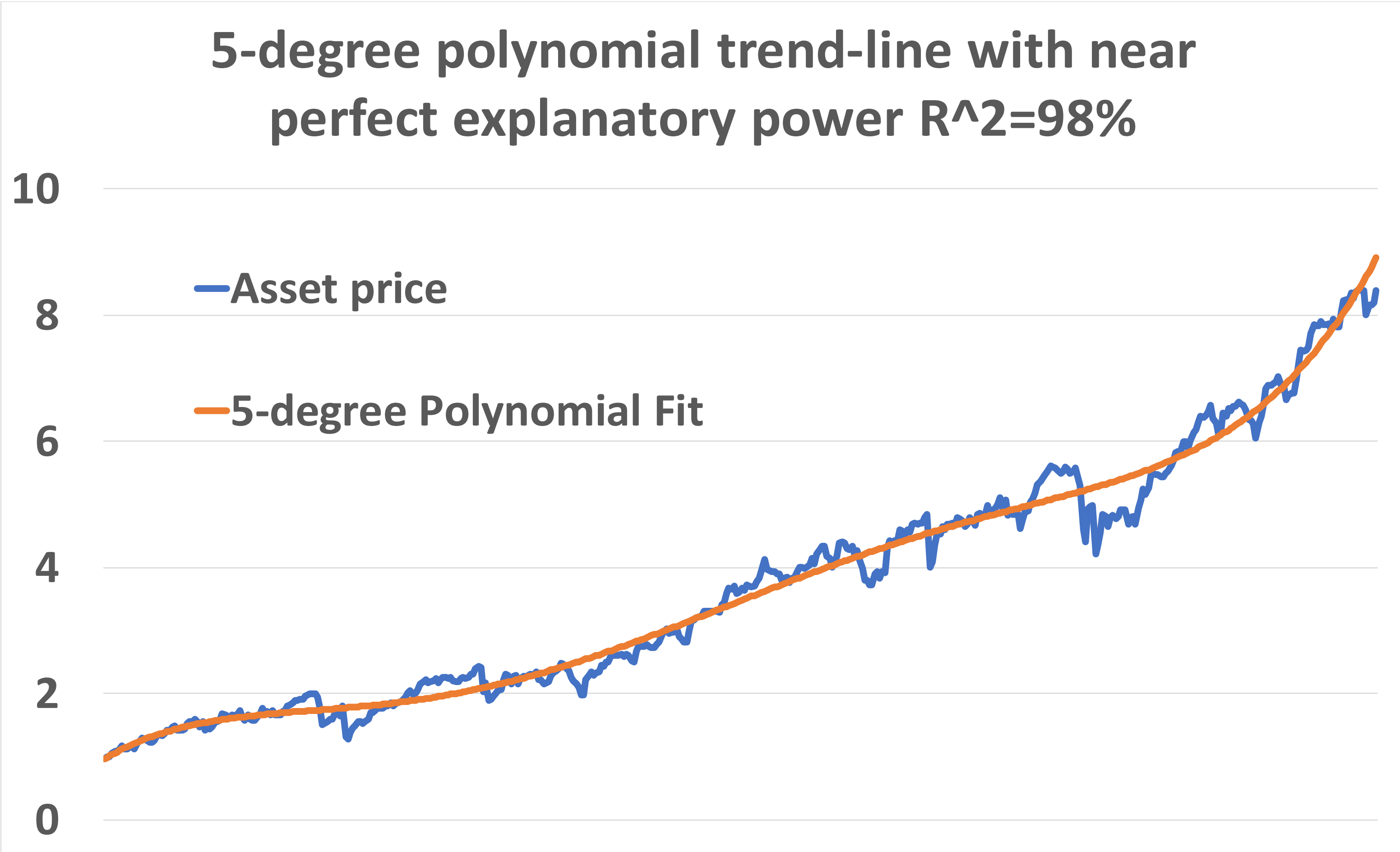
Machine Learning for Quant Strategies

- Theoretical foundations of Machine/Statistical Learning:
  - Approximation vs Estimation error
  - Simplicity vs Complexity
- Why Alternative Risk Premia products failed
- Example of supervised learning for selecting volatility models
- Risk-profile of systematic investment strategies

Data Overfitting: many solutions to fit data points locally with different global behaviour

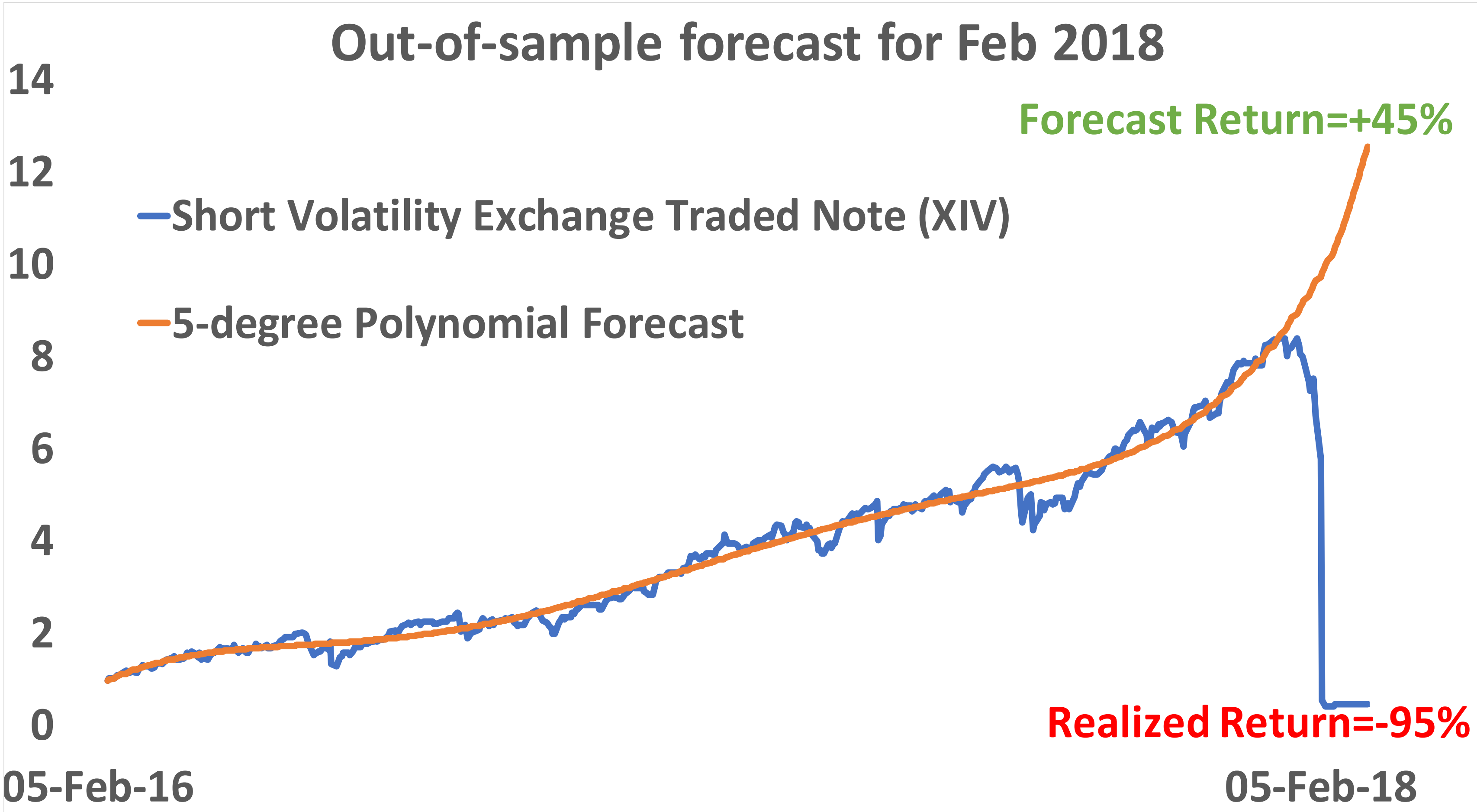


Example of perfect in-sample fit for an asset price path



Example of out-sample forecast for short vol ETN

- How to prevent ML algorithms from falling into this trap?



Credit derivatives crisis in October 2008

- Quant models for credit derivatives relied on multi-parameter models with linear fits: one parameter for market price of each instrument
- The models failed to calibrate and work in distressed markets during the Financial Crisis

S&P 500 Index Daily Movers

Gainers	% ↓	Losers	% ↑
WMT	0.30%	AIG	-23.10%
MCD	0.23%	MER	-19.56%
KO	0.11%	LEH	-19.29%
		GNW	-18.64%
		ACAS	-18.17%
		GE	-17.97%
		DDR	-17.10%
		HIG	-16.86%

Alternative risk premia (ARP) crisis in October 2018

- ARP is marketed by major banks as market-neutral using overstated back-tests
- ARP products proliferated from 2015 with estimated AuM $500 bln at mid of 2018
- Performance of live ARP products from 2015 has been less spectacular than back-tests

HFR Bank Systematic Risk Premia Indices October 2018 YTD Performance

Gainers	YTD % ↓	Losers	YTD % ↑
Rates Momentum Index	7%	Multi-Asset Value Index	-61%
Credit Multi-Style Index	5%	Multi-Asset Volatility Index	-34%
Rates Value Index	4%	Equity Volatility Index	-27%
Currency Volatility Index	4%	Equity Multi-Style Index	-26%
Credit Carry Index	1%	Credit Momentum Index	-22%
		Multi-Asset Multi-Style Index	-21%
		Multi-Asset Index	-20%
		Equity Size Index	-19%
		Multi-Asset Momentum Index	-17%
		Equity Index	-16%
		Equity Quality Index	-16%
		Commodity Volatility Index	-14%
		Equity Carry Index	-13%
		Commodity Multi-Style Index	-13%
		Equity Value Index	-13%
		Commodity Smart Beta Index	-11%
		Equity Momentum Index	-11%
		Equity Smart Beta Index	-10%
		Trend-Following Index	-10%
		Currency Carry Index	-8%
		Credit Index	-8%

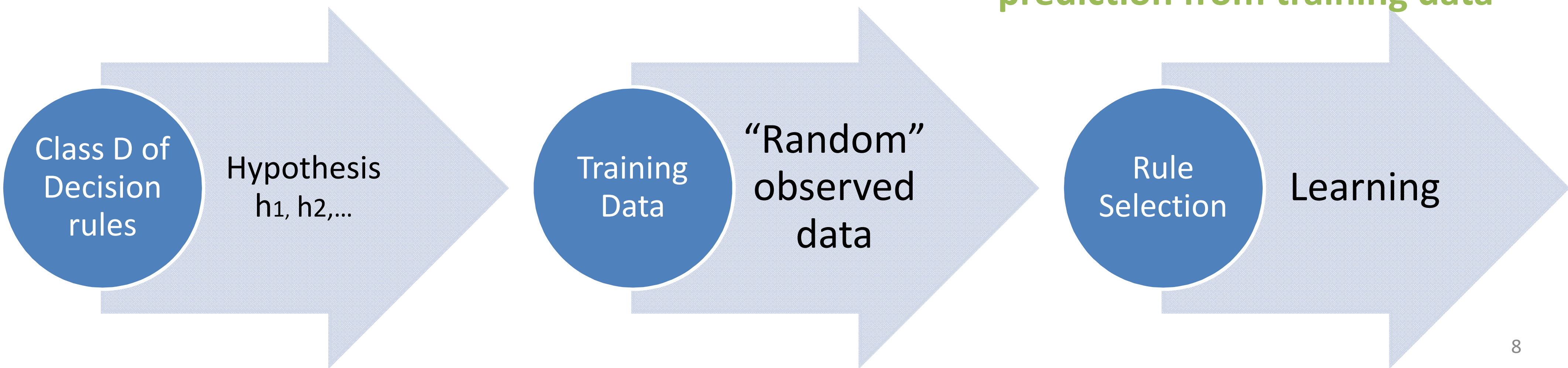
Rich class of decision rules may reduce the approximation error but increases the estimation error

Bayesian learning: select the rule with the highest posterior probability but prior probabilities are needed(!)

Probably Approximately Correct (PAC) learning: if class D is PAC learnable there exists a finite sample size of for given level of approximation and estimation error

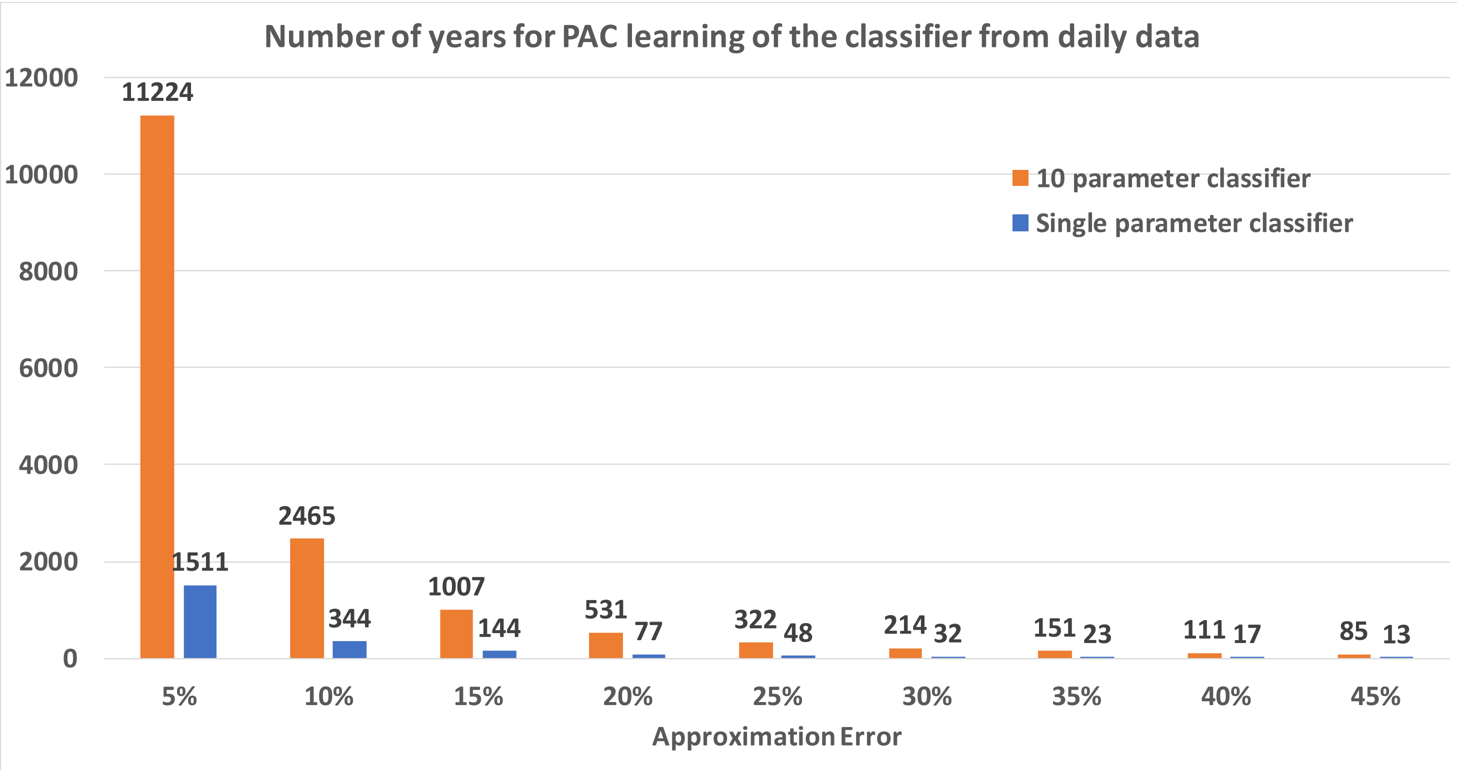
Approximation error: the class D may not have good rules

Estimation error: we are unable to identify the good rule for prediction from training data



Vapnik-Chervonenkis (VS) dimension measures the richness of the class of decision rules

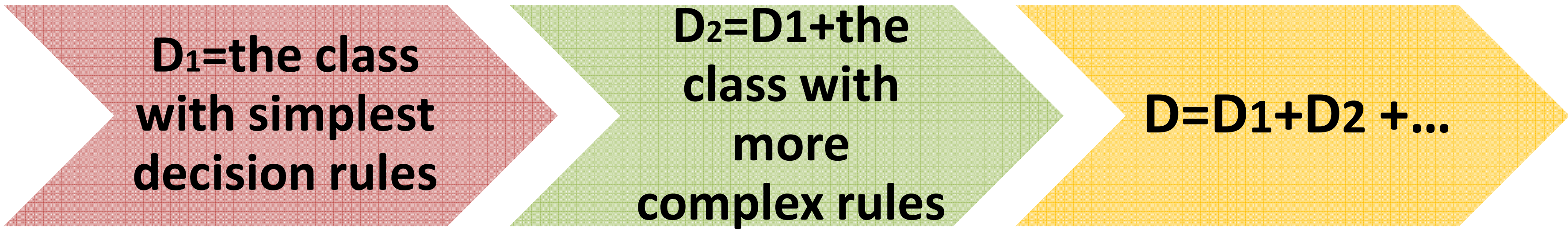
- VC dimension predicts the bounds of the sample size for PAC learning
- Example using single-parametric threshold classifier: buy if last return is higher than threshold, sell otherwise: the VC dimension is one



PAC learning using Hierarchy of Decision rules

- Restricting the richness of the class may improve PAC learning but may increase the approximation error
- Split the class D of all decision rules into a sequence of classes D_i which are PAC learnable
- VC dimension is a measure of the complexity of rules in class D_i
- Select a rule by minimizing:

Approximation Error + Complexity



PAC learning for the process of systematic trading includes at least three classes of decision rules

Signal

Look for predictors with highest scores

Portfolio

Manage risk allocation and diversification

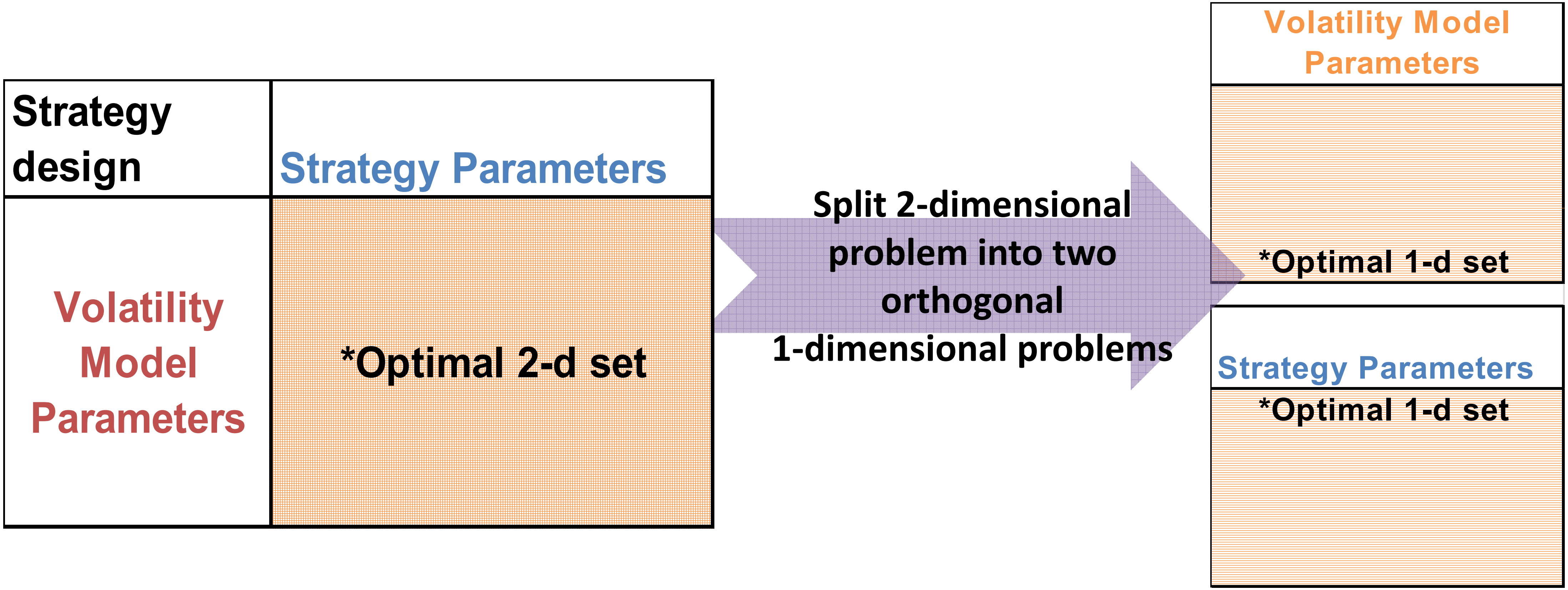
Execution

Minimize trading costs and slippage

- Examples of inconsistent trading processes

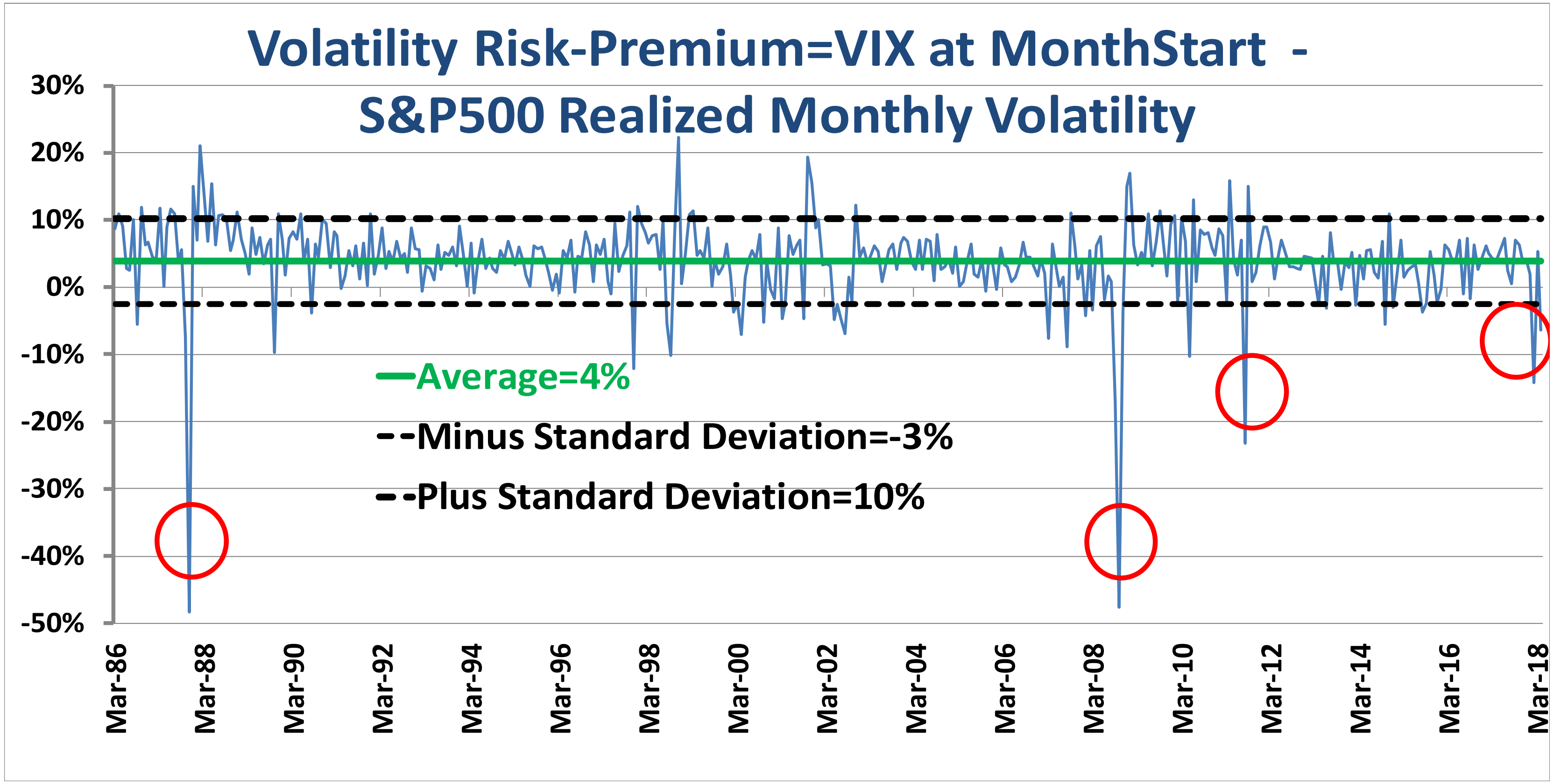
1. Signal that works only on one asset: cannot diversify the portfolio
2. Signal that changes too frequently: execution costs can be too high

Example of designing strategy for volatility trading: learning hierarchy to reduce the dimensionality



Model forecast of realized volatility is applied to estimate the volatility risk-premium

- **Relative value volatility trading:** Sell/buy options with high/low expected spread and delta-hedge



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

Selection of model with the best forecast power

Class of decision rules: all volatility models

Implementation: use 40 models from 4 model classes

Uniform metric for model selection

Implementation: distribution tests for the stability of the forecast

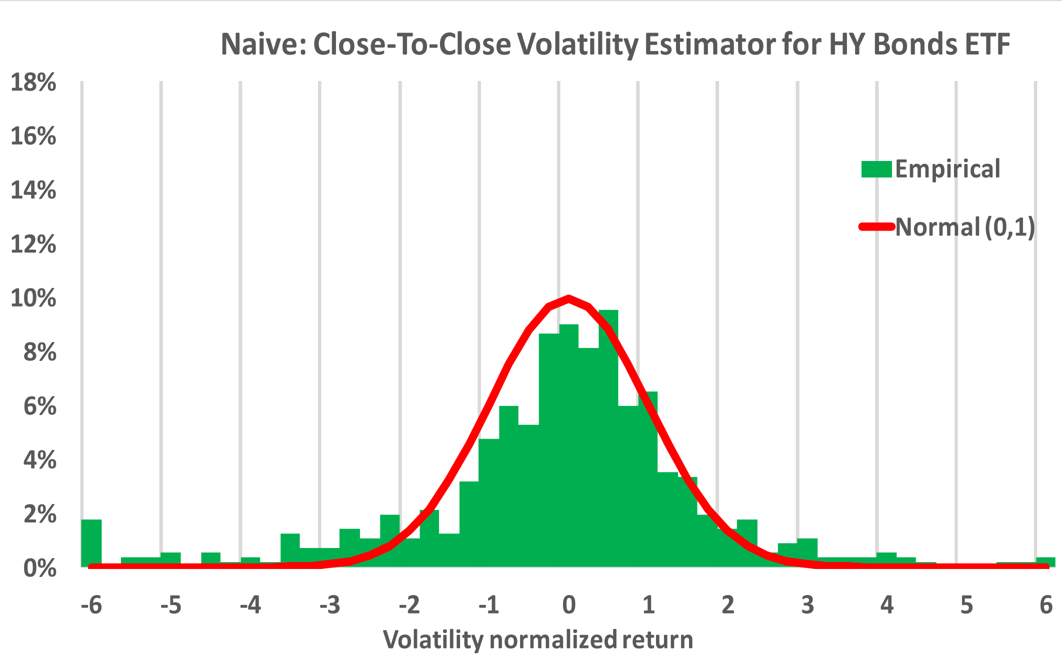
Select model with the highest score for the asset or asset class

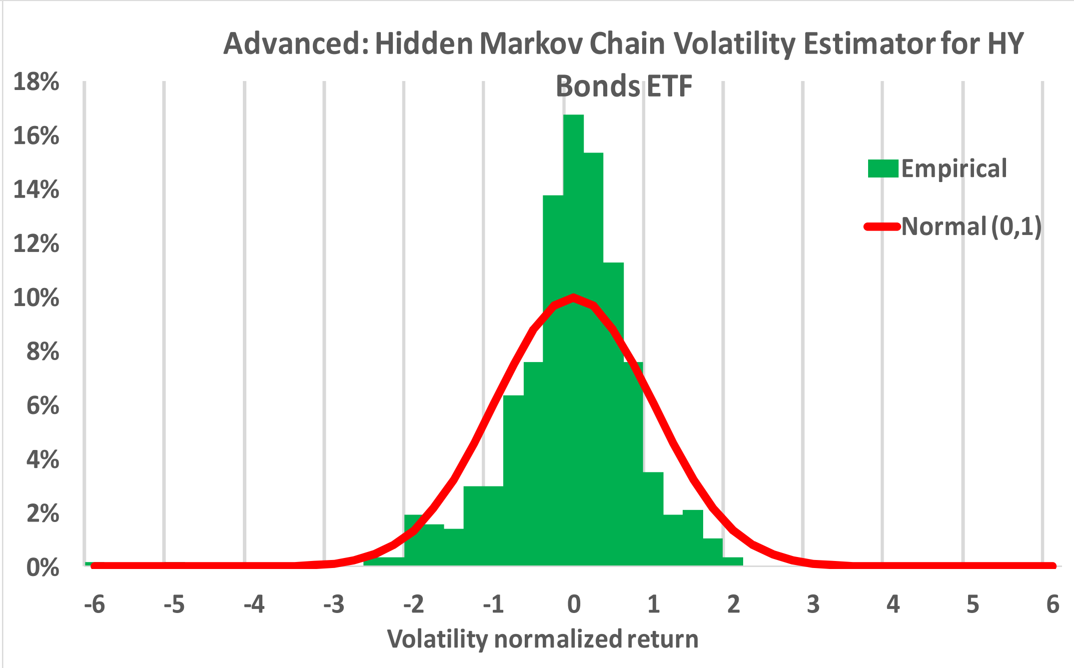
Implementation: Regularly update the tests as new data is available

Distribution tests is applied for volatility normalized returns over forecast period

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

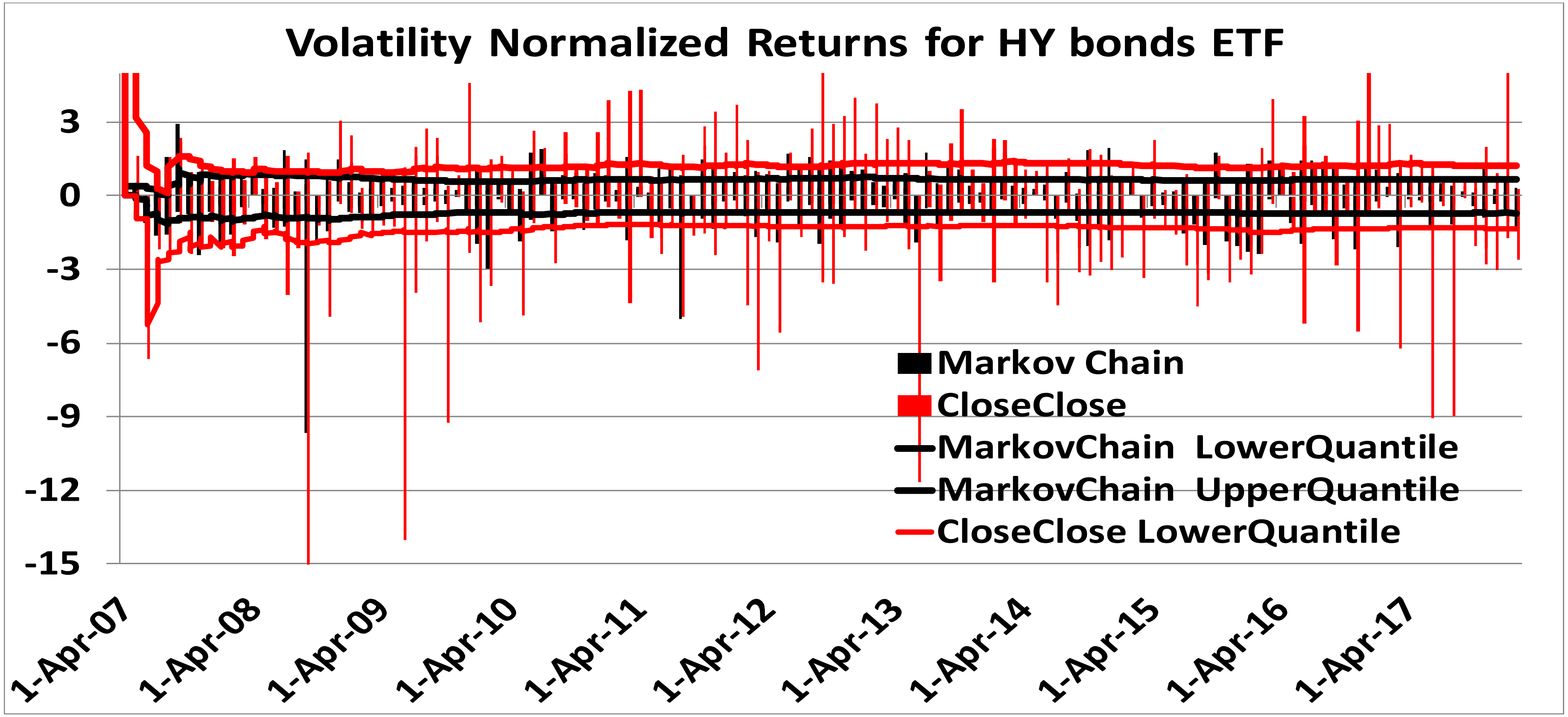
For a model with strong predicative power, sample distribution of Z(n) is symmetric with standard deviation of 1 (unbiased forecast)





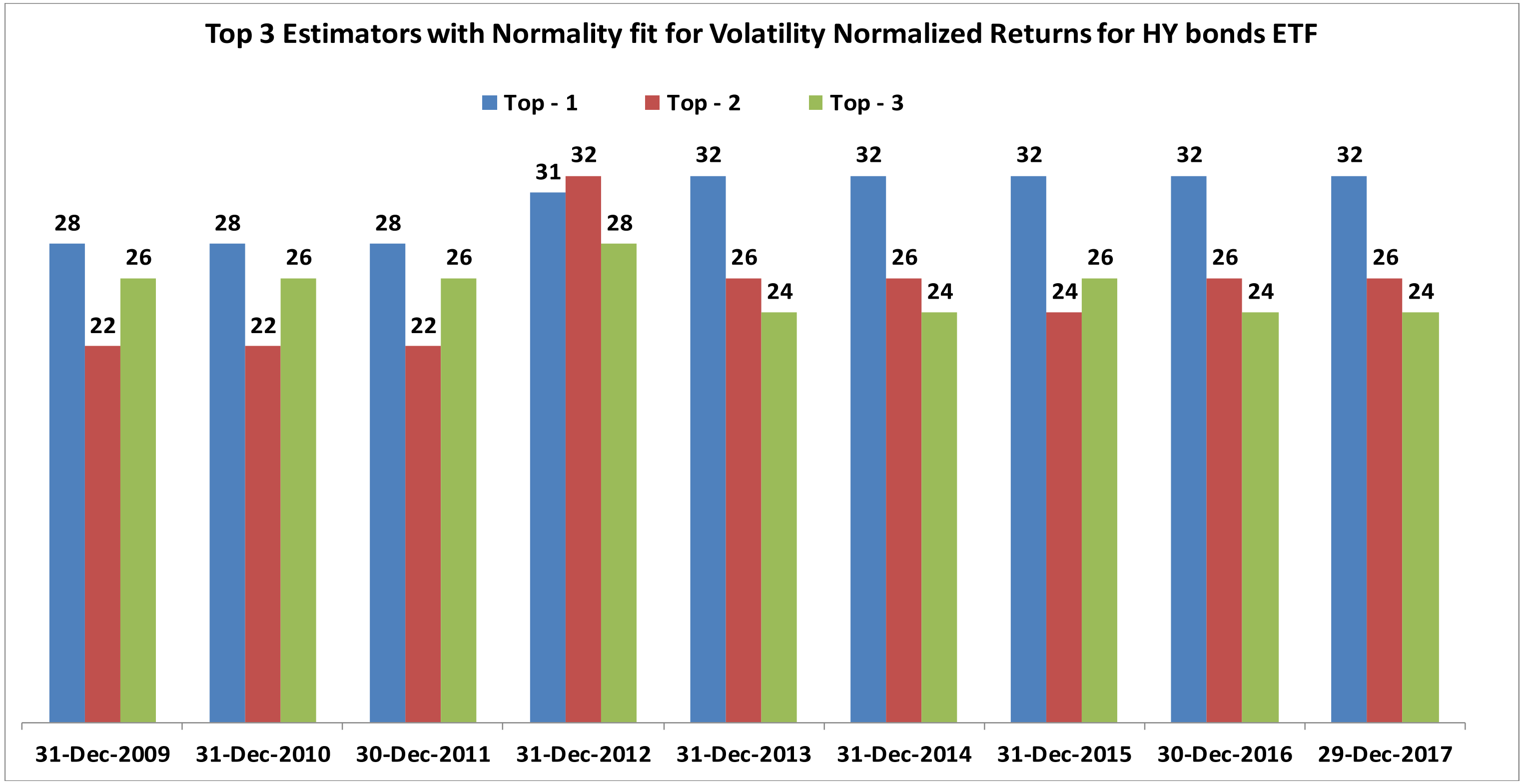
Robust estimator provides tight bounds for volatility forecast with no "surprises"

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



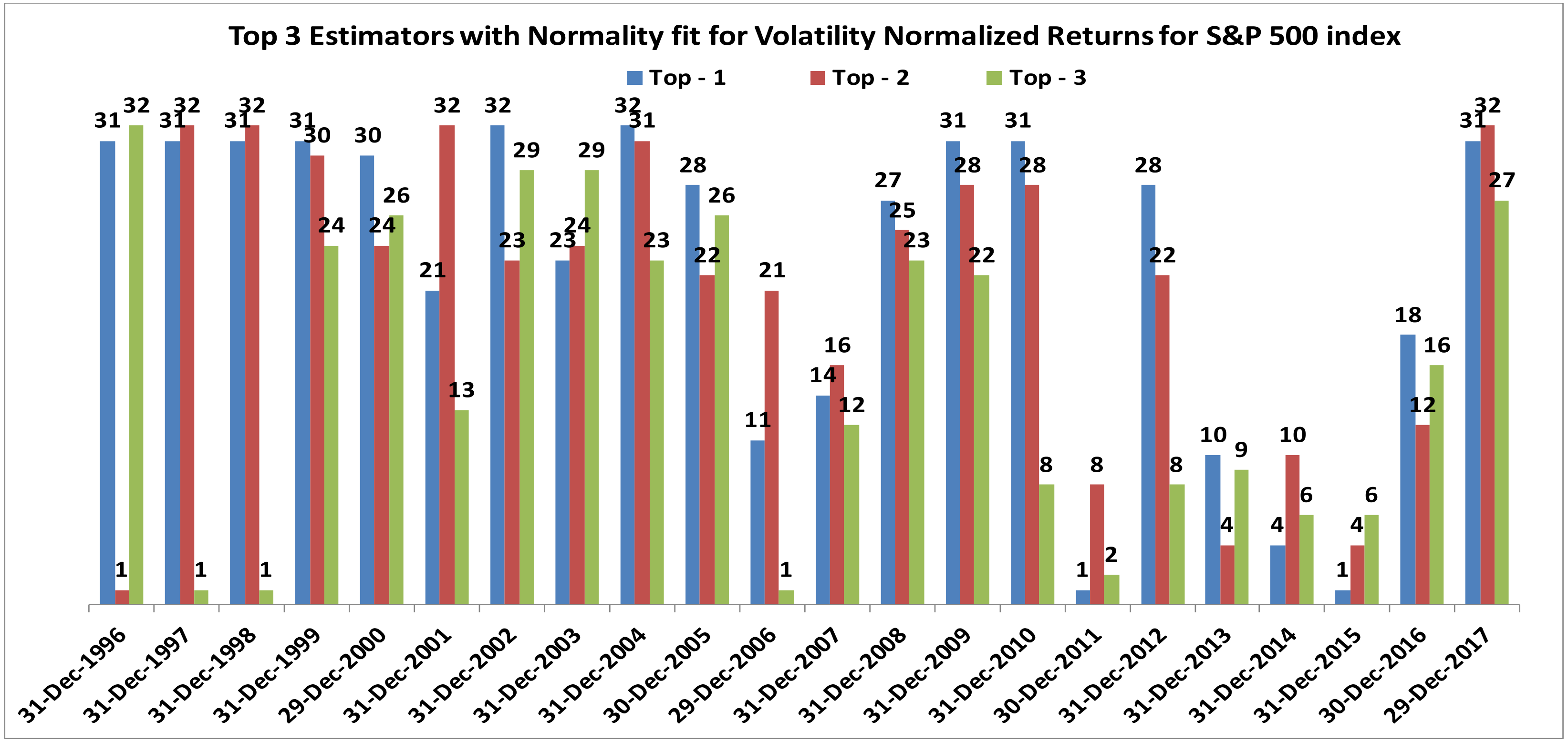
Top-3 models for High Yield Bonds ETF using the normality test annually

- Use past rolling window of 3 year for one step forecast evaluation
- Each model is numbered (1,2,…)
- Stable ranks for Markov chain (31-32) and GARCH models (21-30)



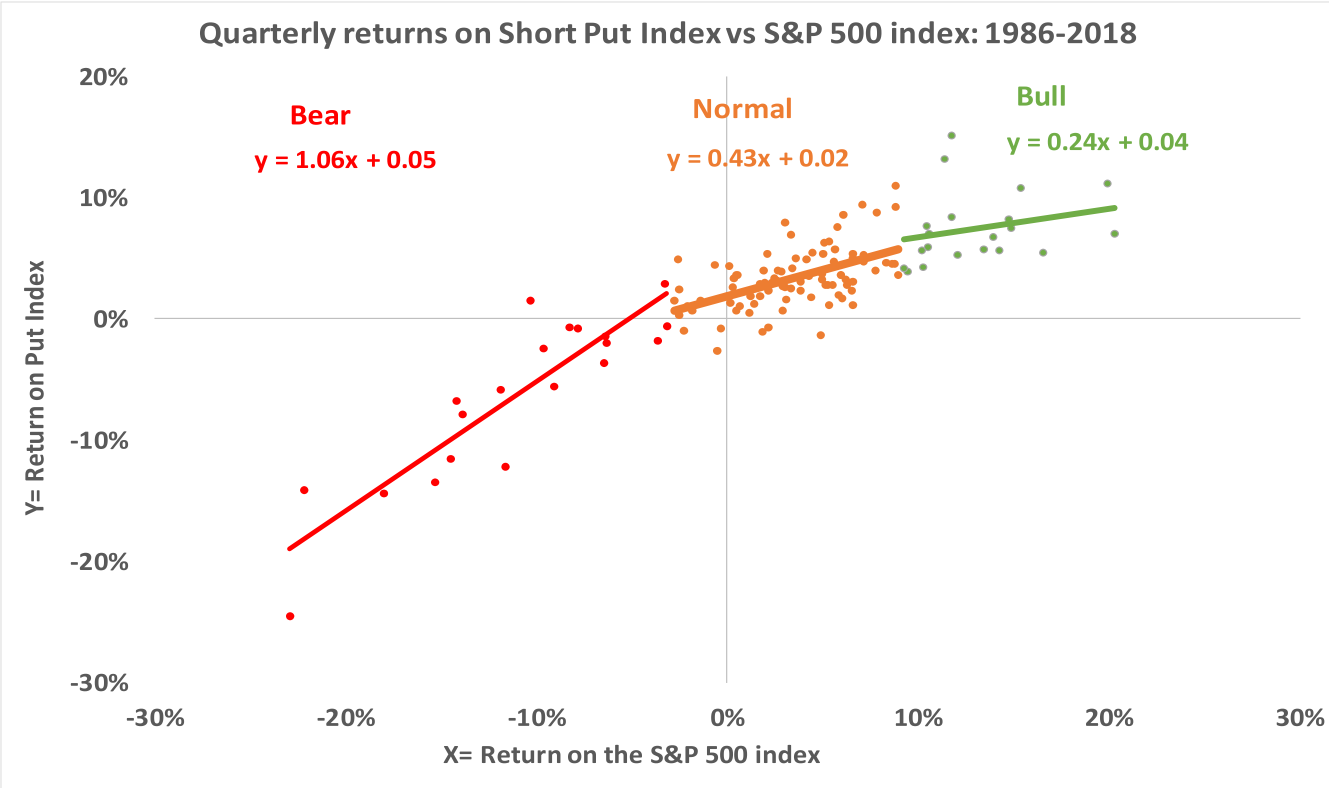
Top-3 models for the S&P 500 index using normality test in walk-forward analysis annually

- Markov Chain models (31,32) are frequently on the top
- Intraday estimators (1-10) are also reliable while being least complex



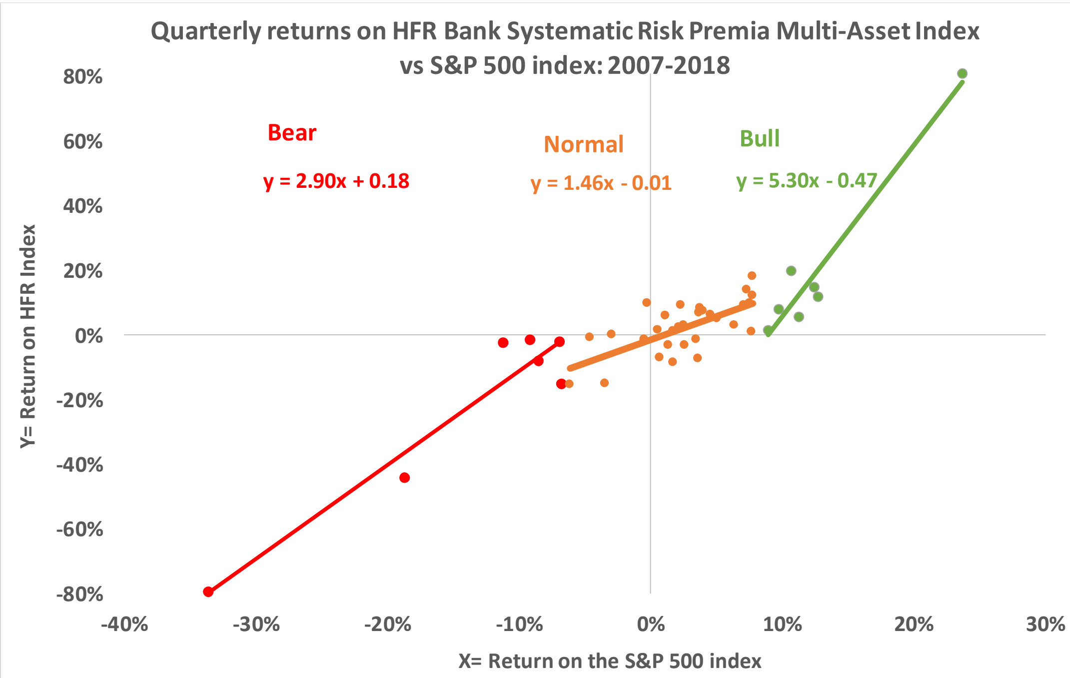
Quantitative Strategies have changing profile in different market regimes

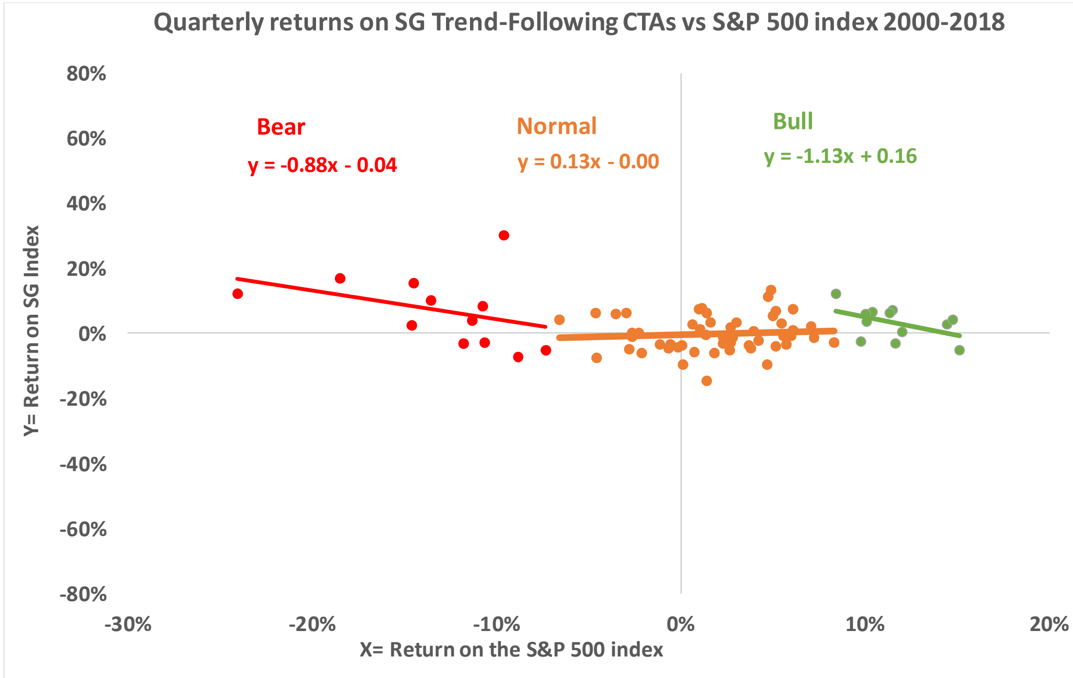
- Apply the quantile regression of returns on the strategy vs returns on the benchmark
- Three regimes: bear, normal, and bull
- Example using CBOE Put index selling at-the-money put options on the S&P 500 index



Risk profile of HFR Bank Systematic Risk Premia Multi-Asset Index vs SG Trend-following CTAs

- Bank Risk Premia Index is short 3× leveraged put and long 5× leveraged call
- Trend-following CTAs replicate protection for bear regimes with overall positive performance
- The difference between amateur and professional applications of ML methods





Conclusions: Machine Learning for Quant Strategies

- Machine/Statistical learning models are as good as people behind them
- Nested approach for strategy design to balance between complexity and approximation & estimation errors
- Understanding of how the strategy behaves in different market regimes
- Models adaptation to different regimes: no free or fixed parameters

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