# Are combination forecasts of S&P 500 volatility statistically superior? Ralf Becker, Adam E. Clements (2008)

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December 15, 2023

## Paper overview

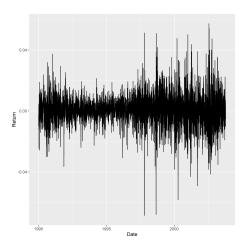


Figure: Daily returns S&P 500 (1990-2003)

- Volatility of high-frequency returns usually not constant over time
- Apply rolling-window procedure to test volatility models
  - Fit: 1000 data points
  - Forecast horizon: 22 days (equivalent to VIX prediction)
- Compare to implied volatility (VIX)
- Combine models to assess whether they perform better than single models

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# Narrow replication

• Model (de-meaned) returns  $Y_t$  as function of  $\sigma_t$  (conditional standard deviation) and  $\epsilon_t$  (mean zero random process):

$$\begin{aligned} Y_t &= \sigma_t \epsilon_t, \ \epsilon_t \sim \textit{N}(0,1) \\ E_{t-1}[Y_t^2] &= E_{t-1}[\sigma_t^2 \epsilon_t^2] = \sigma_t^2 \end{aligned}$$

 Perform rolling-window procedure and compare performance of models (subset of models used in paper)

#### ARCH(1)

$$\sigma_t^2 = \gamma + \alpha \cdot y_{t-1}^2$$

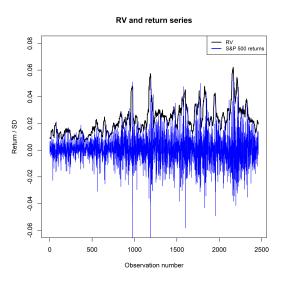
### Garch(1,1)

$$\sigma_t^2 = \gamma + \alpha \cdot y_{t-1}^2 + \beta \cdot \sigma_{t-1}^2$$

#### GJR-Garch(1,1)

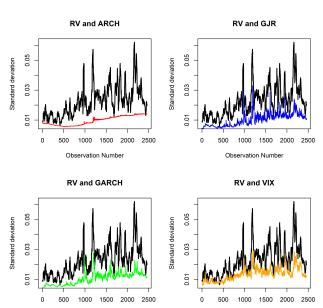
$$\sigma_t^2 = \gamma + (\alpha + \delta 1_{(y_{t-1} < 0)}) \cdot y_{t-1}^2 + \beta \cdot \sigma_{t-1}^2$$

## Results I



Model	MSE
ARCH(1,1)	0.618
GJR-Garch(1,1)	0.534
Garch(1,1)	0.532
VIX	0.356

Table: Model results (out-of-sample)



# Reflection and further steps

#### Reflection

- Authors do not provide data and code
- Models incorporating realized volatility cannot be estimated
- Chosen benchmark not optimal given its stochastic nature
- Results cannot directly be compared to paper (very sensitive to benchmark)

## Further steps

- Choose a different benchmark (e.g. intraday low-to-high ratio)
- Extend models by adding more lags
- Various Garch extensions are possible
- Change distribution of  $\epsilon_t$  (e.g. log-normal or other heavy-tail distribution)