# FTSE 100 Returns and Volatility estimation using Higher Order Neural Networks

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## Overview

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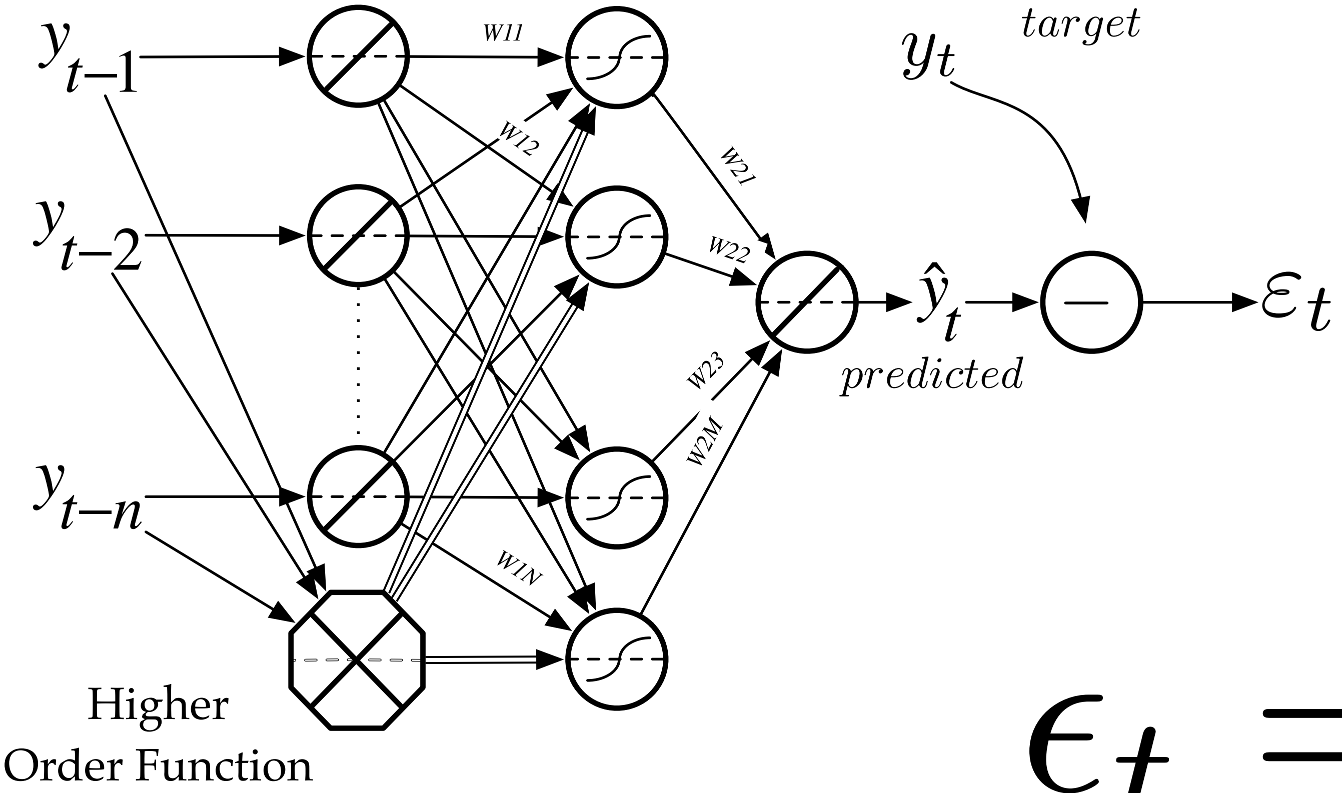
## Introduction

- Returns and Volatility
- Trading *decisions*
- *ARMA-GARCH* widely used in literature
- Financial data is *complex* and *non-linear*

# Modelling Returns

## Neural Network



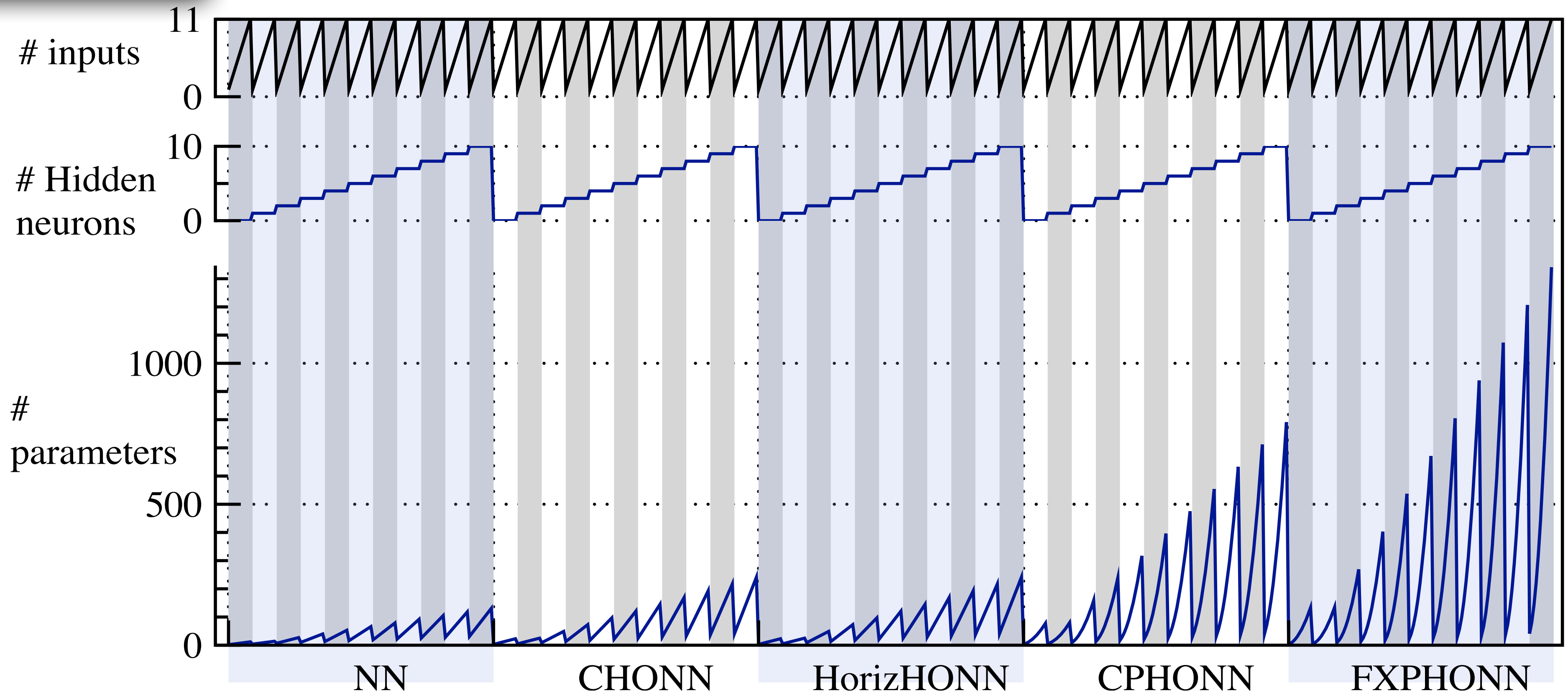

*residual*

$$MSE = \min_W \left(\frac{1}{N} \sum_{t=1}^{N} \epsilon_t^2\right)$$

$$J = \frac{\delta Layer}{\delta W_{Layer}}$$

$$W_{new} = W_{old} - [\nabla^2 J - \mu I]^{-1} J \epsilon$$

$$\epsilon_t = \sigma z_t$$




$$FXPHONN = \begin{bmatrix} y_1 \times y_1 & y_1 \times y_2 & \cdots & y_1 \times y_m \\ y_2 \times y_1 & y_2 \times y_2 & \cdots & y_2 \times y_m \\ \vdots & \vdots & \ddots & \vdots \\ y_n \times y_1 & y_n \times y_2 & \cdots & y_n \times y_m \end{bmatrix}$$

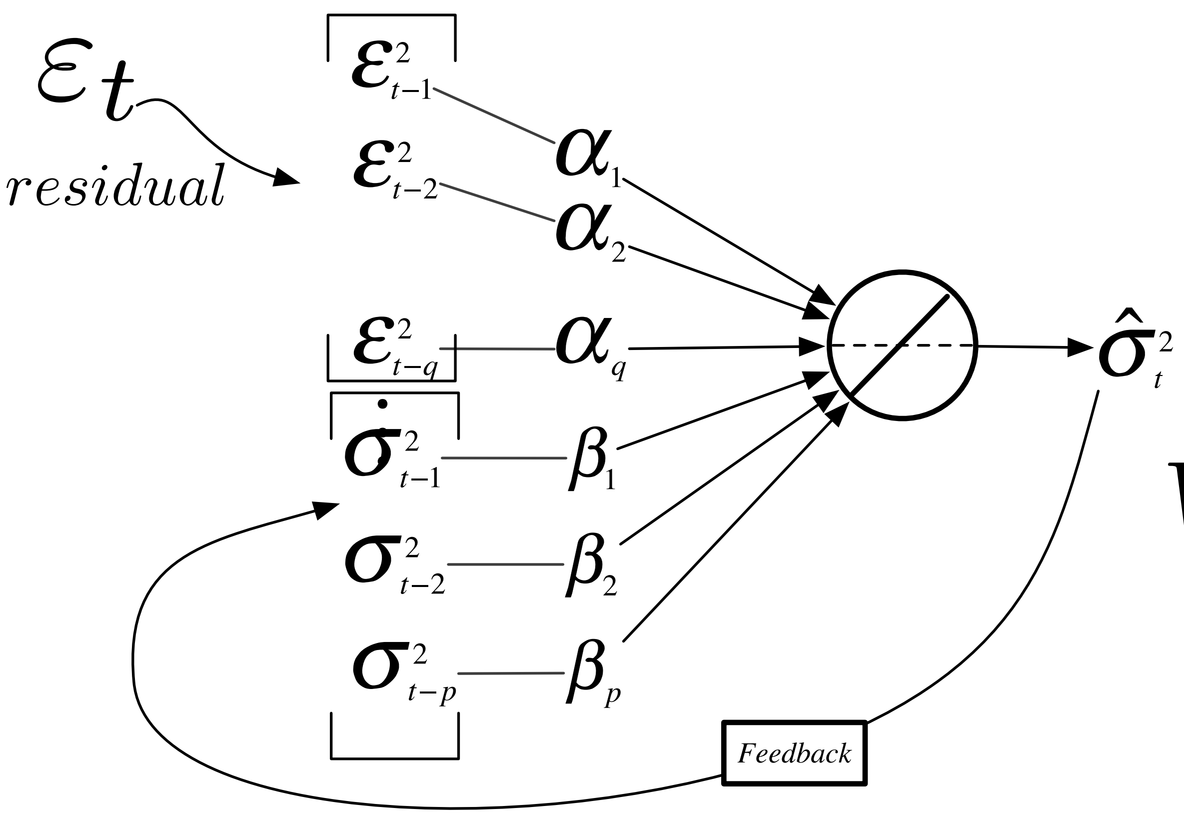
**HONNs are functions of the FXPHONN**

# Modelling Volatility

Generalised AutoRegressive Conditional Heteroskedasticity (GARCH)

$$\epsilon_t = \sigma_t z_t$$

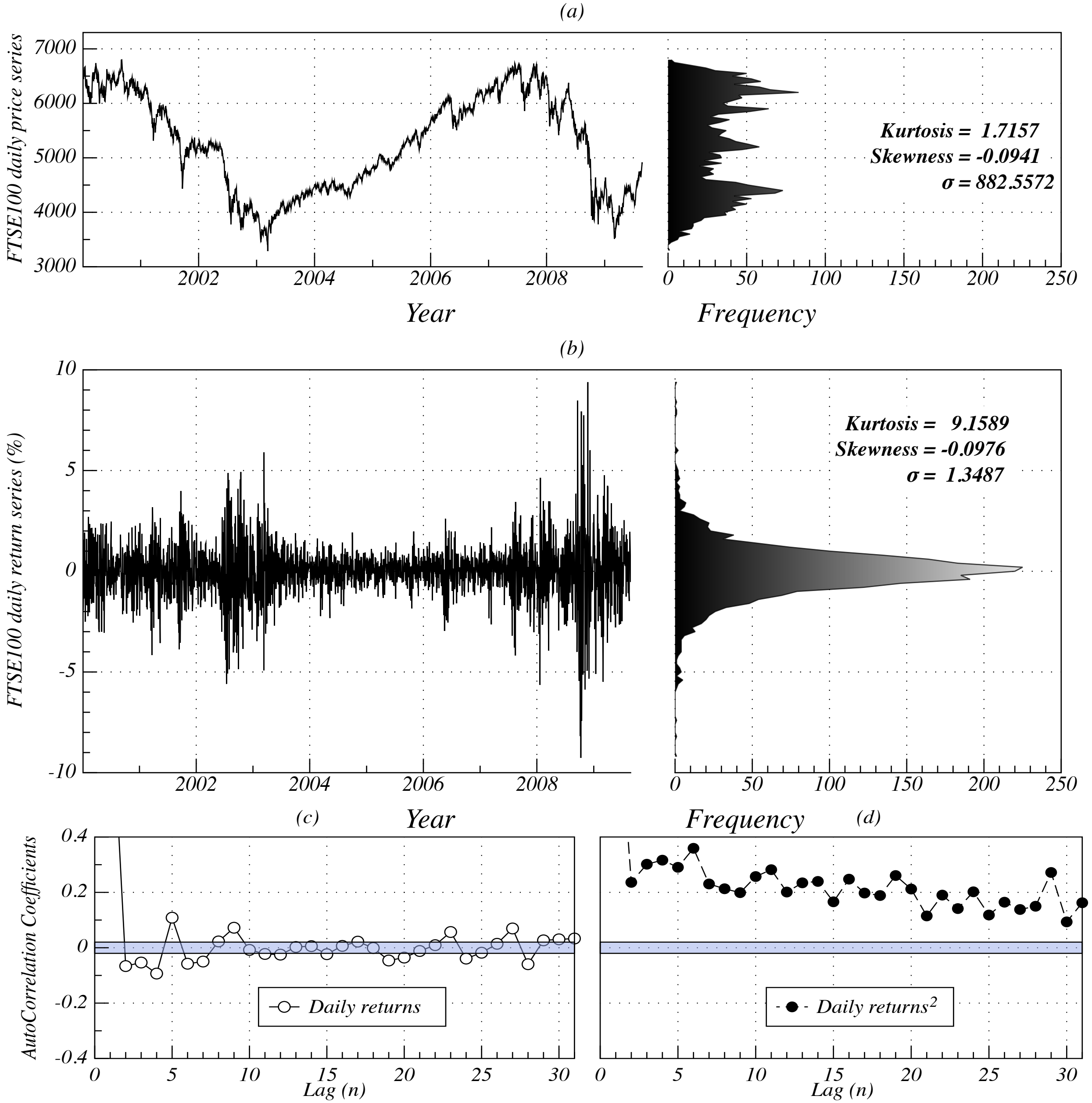
$$LLF = \frac{1}{2}\sum_{t=1}^{N}(log(2\pi\sigma_t) + \frac{\epsilon_t^2}{\sigma_t})$$



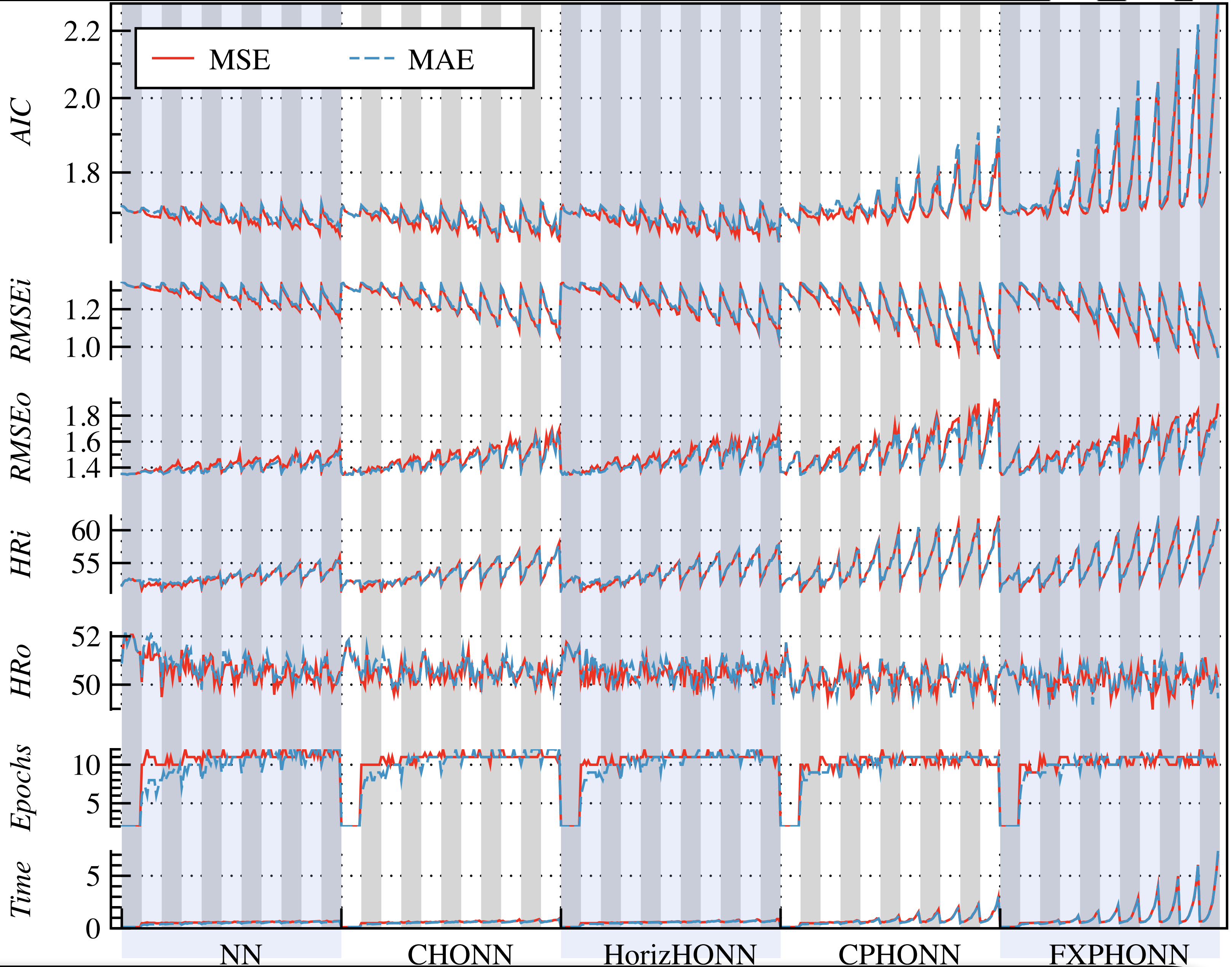

*Volatility*

# Data

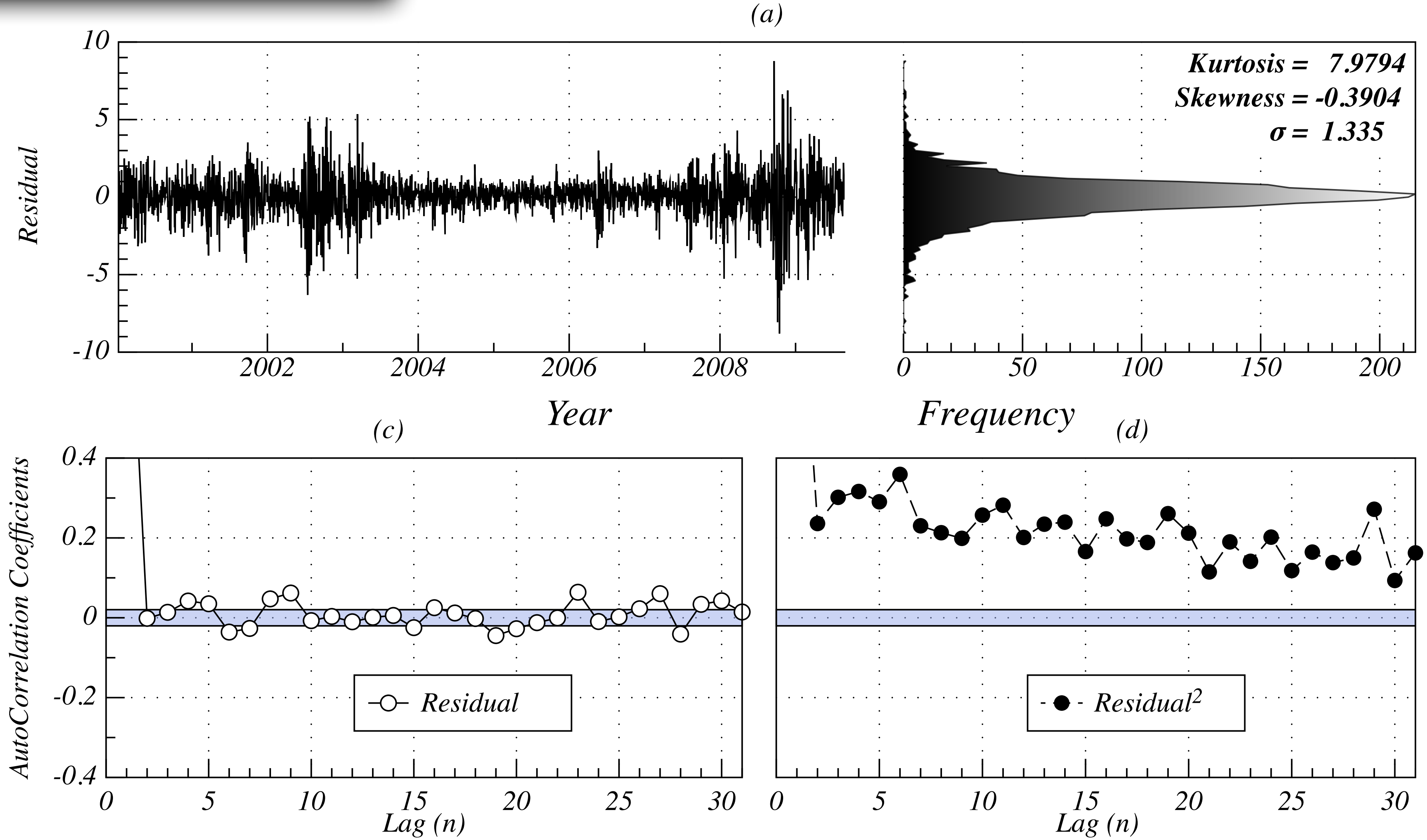
$$r_t = 100 \times (log(p_t) - log(p_{t-1}))$$



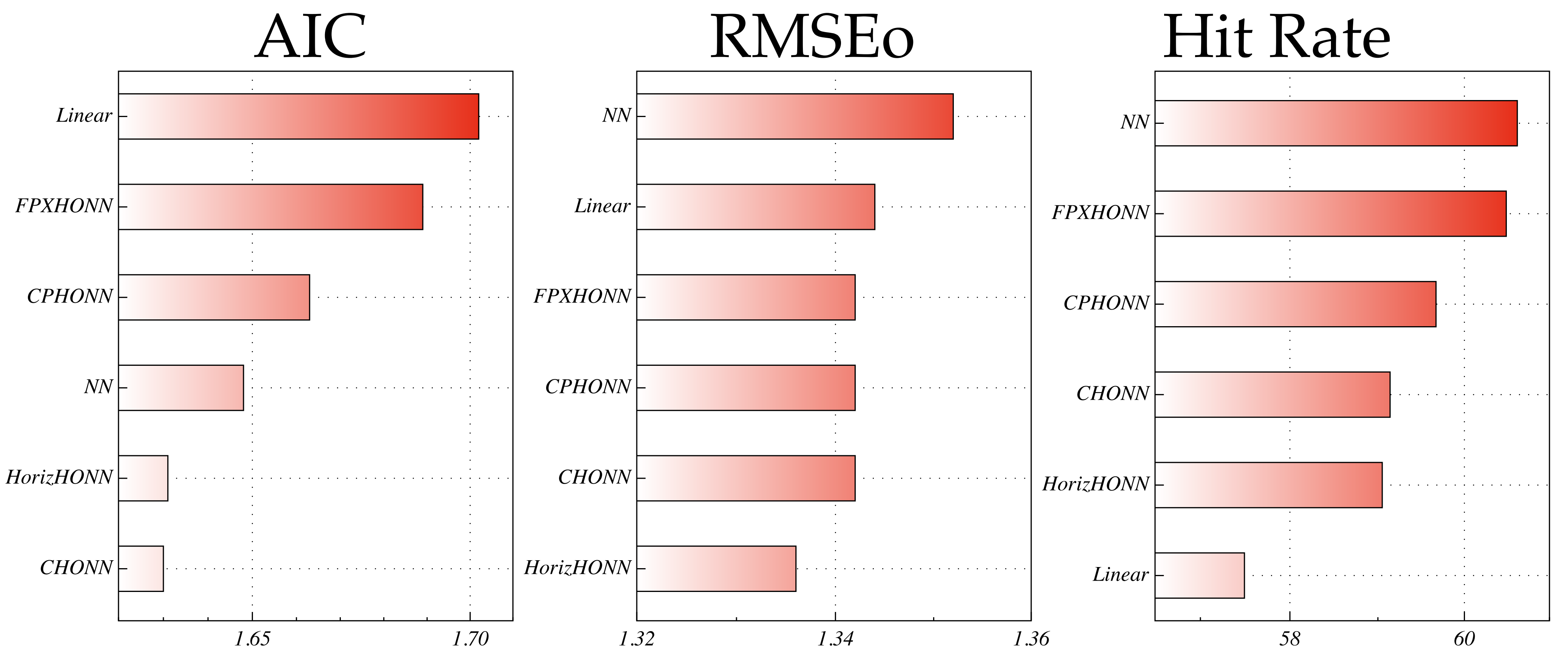
# Simulations



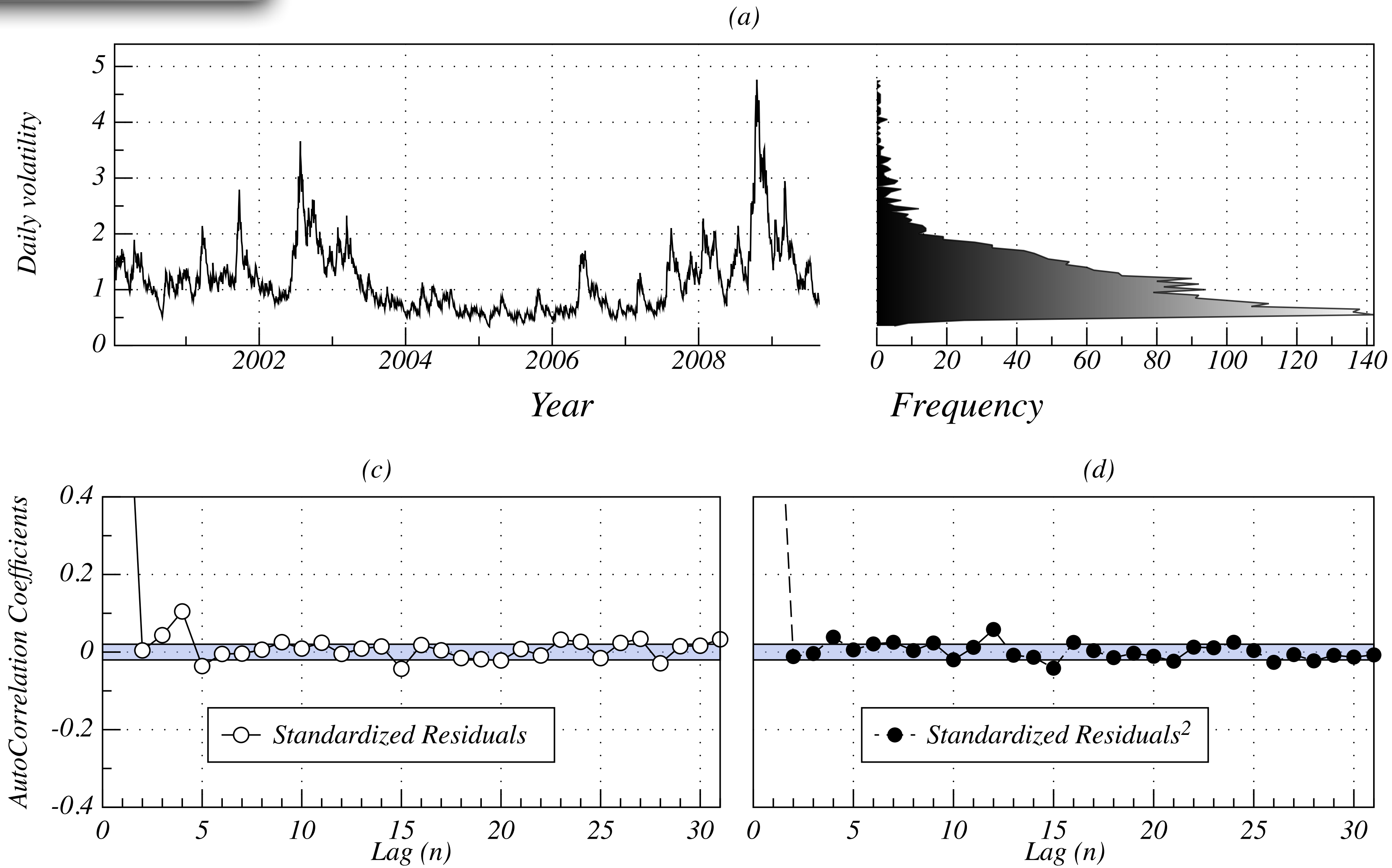
# Results: Returns



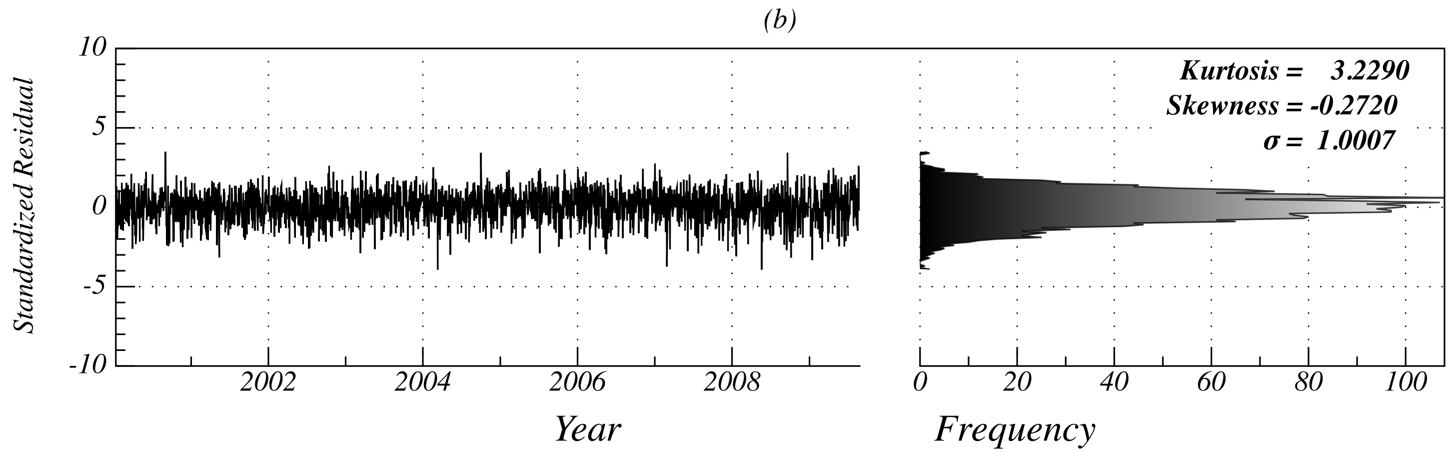
# Results: Returns 2

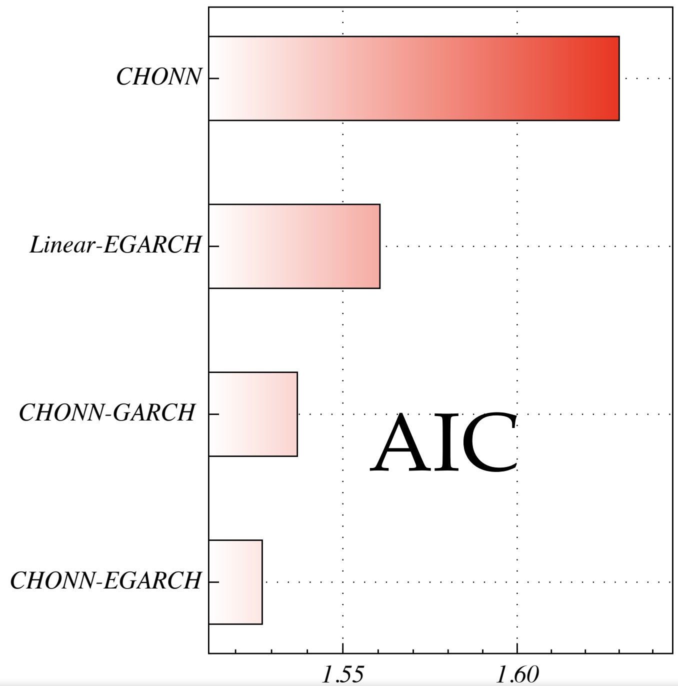


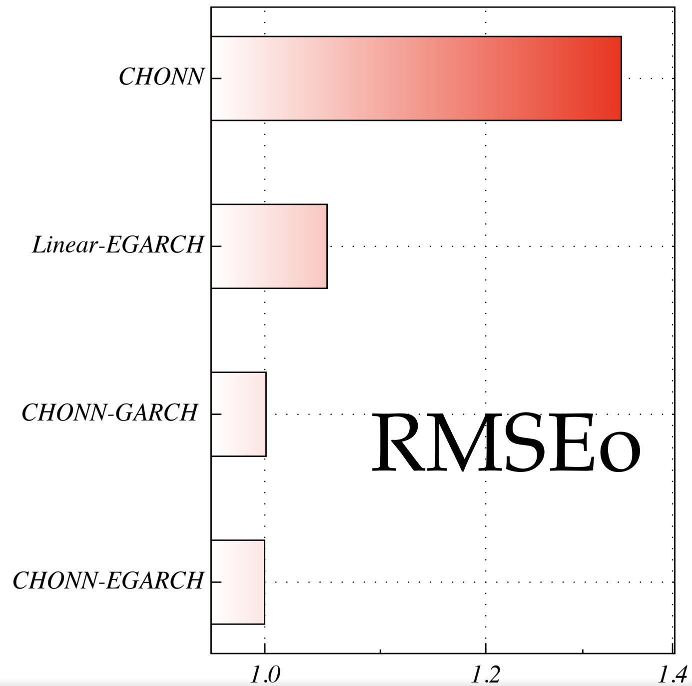
# Results: Volatility



# Results: Volatility 2



## Conclusions

- Higher Order Neural Networks allow for better results compared to Linear models
- Most effective when used to model returns
- NNs provided highest Hit Rates
- Small models give better out-of-sample results
- A combination of HONNs and Volatility estimation models least error and no volatility

## Acknowledgements

I would like to thank University College London (UCL), for awarding Overseas Research Scholarship (ORS) and Graduate Research Scholarship (GRS) funding.

# Q&A

This work compared Higher Order Neural Networks (HONN) with Neural Networks, and linear regression for short term forecasting of stock market index daily returns.

Two new HONNs, the Correlation HONN (CHONN) and the Horizontal HONN (HorizHONN) outperform all other models tested in terms of the Akaike Information Criterion, out-of-sample root mean square error, of FTSE100 and NASDAQ giving out-of-sample Hit Rates of up to 60% with AIC improvement up to 6.2%. New hybrid models for volatility estimation are formed by combining CHONN with E/GARCH are compared with conventional EGARCH, providing up to 2.1% and 2.7% AIC improvement for FTSE100 and NASDAQ.

$$\widehat{y}_{t+1} = \beta_0 + \sum_{i=1}^{R} \beta_i \times y_{t-i} + \epsilon_t$$

$$\widehat{y}_{t+1} = y_t$$

$$\widehat{y}_t = \sum_{l=1}^{m} W_{2,l} \times tanh(\sum_{i=1}^{m} W_{1,i} \times y_{t-i} + b_1) + b_2$$

$$MAE = \frac{1}{N} \sum_{t=1}^{N} |y_t - \widehat{y}_t|$$

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

$$CPHONN = H_{i,j},\ i : 1 \rightarrow n,\ j : i \rightarrow n$$

$$CHONN = \left( \sum_{i=1,j=i}^{n} H_{i,j} \quad \sum_{i=2,j=i}^{n-1} H_{i,j+1} \quad \ldots \quad \sum_{i=n,j=i}^{1} H_{i,j+n-1} \right)$$

$$HorizHONN = \left( \sum_{i=1,j=i}^{n} H_{i,j} \quad \sum_{i=2,j=i}^{n} H_{i,j} \quad \ldots \quad \sum_{i=n,j=i}^{n} H_{i,j} \right)$$

$$log\widehat{\sigma}_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{q} L_i S_{t-i}^- \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_j \widehat{\sigma}_{t-j}^2$$

$$S_{t-i}^- = \begin{cases} 1 & \epsilon_{t-i} \leq 0 \\ 0 & \text{otherwise} \end{cases}$$