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# Event Study Analysis of Information Technology Stocks by Dynamic Conditional Score Models

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# Background

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- ❖ This study is born as a continuity from the thesis developed in October, 2014.
- ❖ New models were introduced.
- ❖ Dynamic Conditional Score (DCS) were compared versus ARMA-GARCH Models.

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# Motivation

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- ❖ Prediction over Information Technology (IT) products after special events.
- ❖ Volatility in stock values after a firm releases a product.
- ❖ The 50 best IT products (according to PC World ranking) were analysed in this study.
- ❖ Comparison with DCS models, which effectively control for the outliers of the return distribution.

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# The PC World Ranking

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- ❖ The ranking was not in a particular order.
- ❖ Among the firms present were:
  - ❖ IBM
  - ❖ Microsoft
  - ❖ Apple
  - ❖ Motorola
  - ❖ Canon
  - ❖ HP

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# Objectives

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- ❖ Take an investor's point of view and formulate the question: Is it possible to predict stock price volatility using a previous data set even though there is an important release in the firm?
- ❖ This study compares:
  - ❖ ARMA-GARCH(1,1)
  - ❖ QARMA-Beta-t-EGARCH(1,1)
  - ❖ QARMA-Beta-t-EGARCH(1,1) with leverage models

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# Previous Studies

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- ❖ In 2005, Hansen and Lunde compared nearly 300 ARCH-type to find out which one could be the best out-of-sample volatility predictor.
- ❖ In their study, they analysed the IBM stock and the German Mark versus American Dollar exchange rate.
- ❖ For the DM/USD exchange rate, there is no evidence that GARCH(1,1) is outperformed by more sophisticated models. However, for the IBM stock, they find that GARCH(1,1) is inferior to several models that accommodate leverage effects.

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# Data

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- ❖ To begin, the 50 most important products were taken into consideration. Those products were the ones in the PC World ranking.
- ❖ Not all data could be retrieved for some stocks. Reasons could be: Company not in the Stock Exchange, company outside US, company bought, among others.

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# Data

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- ❖ 19 products were taken into account, finally.
- ❖ Data was collected for the period before and after for those products. (Before-the-release-period and After-the-release-period).
- ❖ 430 and 215 were the number of samples for each stock. This was because of BlackBerry had the shortest data period available for model estimation.



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# Data

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- ❖ For both estimation and forecast windows, the daily log return was computed.
- ❖ We measure the market-specific component by the daily log return on the Standard and Poor's 500 (S&P 500) stock index, S&P500.

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# The Models

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- ❖ The comparison was made among:
  - ❖ ARMA(p,q)-GARCH(1,1) [Benchmark]
  - ❖ QARMA(p,q)-Beta-t-EGARCH(1,1)
  - ❖ QARMA(p,q)-Beta-t-EGARCH(1,1)-leverage model

# ARMA(p,q)-GARCH(1,1) [Benchmark]

$$y_t = \mu_t + v_t$$

$$v_t = \sigma_t \epsilon_t$$

$$\mu_t = \omega + \gamma \text{S\&P500}_t + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \theta_j v_{t-j}$$

$$\sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 v_{t-1}^2$$

# QARMA(p,q)-Beta-t-EGARCH(1,1)

$$y_t = \mu_t + v_t$$

$$v_t = \exp(\lambda_t)\epsilon_t$$

$$\mu_t = \omega + \gamma \text{S\&P500}_t + \sum_{i=1}^p \phi_i \mu_{t-i} + \sum_{j=1}^q \theta_j u_{\mu,t-j}$$

$$u_{\mu,t} = \left[ 1 + \frac{v_t^2}{\nu \exp(2\lambda_t)} \right]^{-1} v_t$$

$$\lambda_t = \alpha_0 + \beta_1 \lambda_{t-1} + \alpha_1 u_{\lambda,t-1}$$

$$u_{\lambda,t} = \frac{(\nu + 1)v_t^2}{\nu \exp(2\lambda_t) + v_t^2} - 1$$

# QARMA(p,q)-Beta-t-EGARCH(1,1)-leverage model

$$y_t = \mu_t + v_t$$

$$v_t = \exp(\lambda_t)\epsilon_t$$

$$\mu_t = \omega + \gamma \text{S\&P500}_t + \sum_{i=1}^p \phi_i \mu_{t-i} + \sum_{j=1}^q \theta_j u_{\mu,t-j}$$

$$u_{\mu,t} = \left[ 1 + \frac{v_t^2}{\nu \exp(2\lambda_t)} \right]^{-1} v_t$$

$$\lambda_t = \alpha_0 + \beta_1 \lambda_{t-1} + \alpha_1 u_{\lambda,t-1} + \alpha_1^* \text{sgn}(-v_{t-1})(u_{\lambda,t-1} + 1)$$

$$u_{\lambda,t} = \frac{(\nu + 1)v_t^2}{\nu \exp(2\lambda_t) + v_t^2} - 1$$

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# Leverage Models

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$$\lambda_t = \alpha_0 + \beta_1 \lambda_{t-1} + \alpha_1 u_{\lambda,t-1} + \alpha_1^* \text{sgn}(-v_{t-1})(u_{\lambda,t-1} + 1)$$

- ❖ Considers different effects of positive and negative returns on volatility (Harvey, 2013; Harvey and Sucarrat, 2014).
- ❖ Falling prices increase the risk for stockholders since the debt to equity ratio increases and shareholders only receive cash flows after debtors. Increasing risk due to price falls is termed as leverage effect.

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# Empirical Results

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- ❖ All models are estimated by using data for the estimation window by the Quasi-Maximum Likelihood (QML) method.
- ❖ We determine the optimal order of ARMA and QARMA by comparing a number of alternative specifications by an LL-based model performance metric; which in this case is BIC.
- ❖ We estimate all models with  $p = 0,1,2$  and  $q = 0,1,2,3,4,5$  for the estimation window.

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# Empirical Results

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- ❖ When both  $p = 0$  and  $q = 0$ , then there are no dynamics in conditional location
- ❖ Moreover,  $p = 0$  and  $q > 0$  indicate that MA dynamics are considered, while  $q = 0$  and  $p > 0$  indicate that AR dynamics are considered.



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# Final Discussion

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- ❖ Tables of Results in sheets.

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# References

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Thank you for your attention!

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