

# Adaptive Pointwise Estimation in Conditional-Heteroscedasticity Models

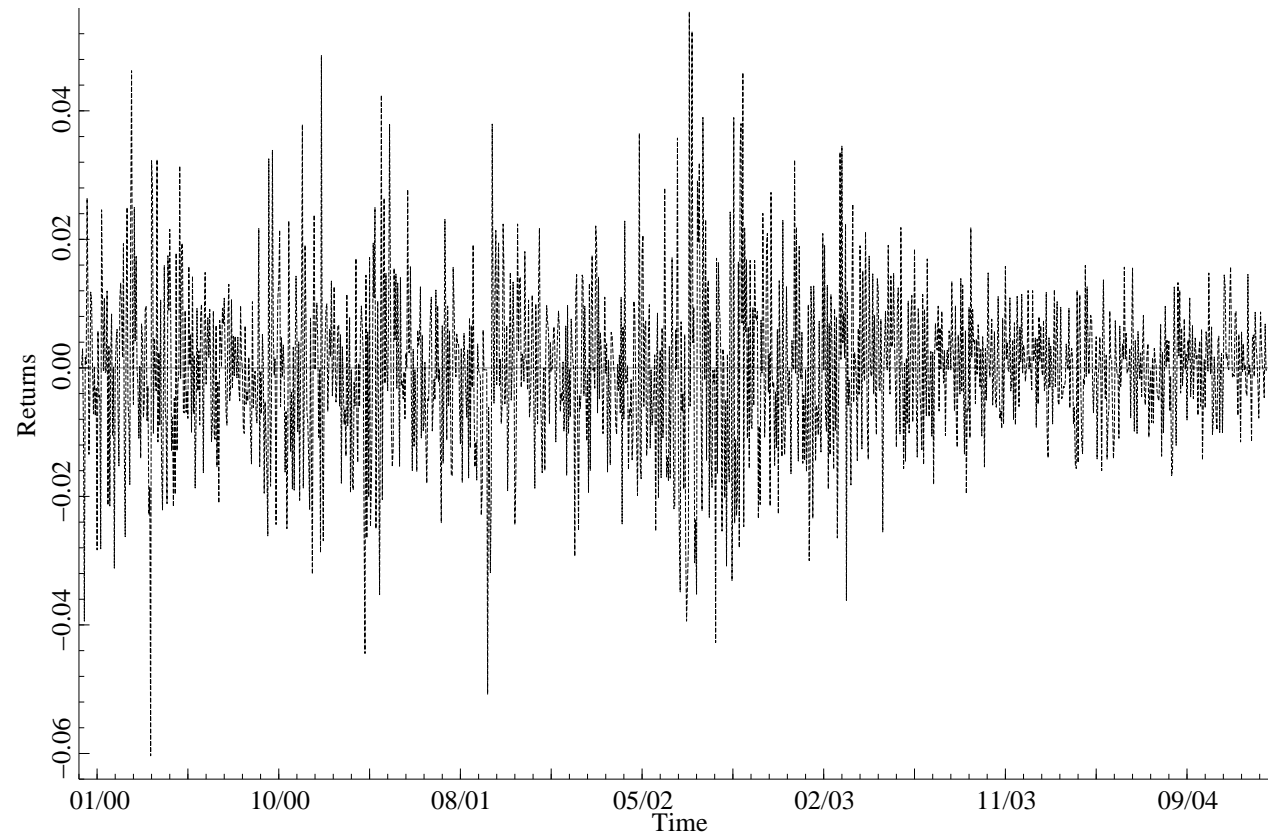
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# Time series regression models

- Time series models
- Structural breaks
- Local parametric modeling
- Adaptive pointwise estimation
- Simulations low
- Simulations high
- Standard & Poors 500 index
- Adaptive ARCH vs. GARCH
- Conclusion

- Classical parametric approach: data follow one model
- Structural breaks and prediction in time series

(S&P500 stock index from January, 2000 to October, 2004)



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## Conditional heteroscedasticity models

- ARCH, GARCH models (Engle, 1982; Bollerslev, 1986)
- stochastic-volatility models (Taylor, 1986)
- time-homogeneous structure

## Structural breaks (change points) in financial time series (Andreou & Ghysels, 2002; Herwatz & Reimers, 2002)

- Breakpoint detection (Mikosch & Starica, 2001)
  - supremum tests (supLR) for GMM (Andrews, 1993)
  - CUSUM-ARCH (Lee et al., 2003)
- Nonparametric time-varying coefficient models
  - parameters smooth in time (Cai, Fan, & Li, 2000)
  - pointwise adaptive (Mercurio & Spokoiny, 2004)

*Extend pointwise adaptive estimation to data-hungry models (e.g., GARCH family)*

# Local parametric modeling

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- Assumption: time series  $Y_t, t = 1, \dots, T$ , follows *locally* some parametric model ( $f_t \in \mathcal{F}$ ; e.g.,  $f_t = f[\theta(t)]$ )

$$Y_t = f_t(Y_{t-1}, \dots, Y_{t-p}, \varepsilon_t, \dots, \varepsilon_{t-q}) \quad (1)$$

- Example of GARCH(1,1)
  - time-homogeneous

$$Y_t = 0 + \varepsilon_t,$$

$$E(\varepsilon_t | \varepsilon_{t-1}) = 0,$$

$$h_t^2(\theta) = \text{Var}(\varepsilon_t | \varepsilon_{t-1}) = \omega + \alpha Y_{t-1}^2 + \beta h_{t-1}^2(\theta),$$

- time-heterogeneous ( $\theta(t) = (\omega(t), \alpha(t), \beta(t))$ ):

$$h_t^2(\theta(t)) = \text{Var}(\varepsilon_t | \varepsilon_{t-1}) = \omega(t) + \alpha(t) Y_{t-1}^2 + \beta(t) h_{t-1}^2(\theta(t))$$

# Adaptive pointwise estimation

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Find the most recent structural break and estimate model on the longest interval of homogeneity “(break, now)”

**1. Initialization:** Start with a short interval  $(t_s, t_e = T)$

**2. SupLR test:** Perform the supLR test (critical values!)

$$\sup LR_{\mathcal{F}}(t_s, t_e) = \sup_{t_s + \Delta L < t_b < t_e - \Delta L} LR_{\mathcal{F}}(t_b; t_s, t_e)$$

**3. Extension:** No break detected

⇒ prolong  $(t_s, t_e)$ , for example by 50%, and go to (2)

**4. Detection:** Break detected at  $t_b \in (t_s, t_e)$

⇒ estimate the model on  $I = (t_b, T)$

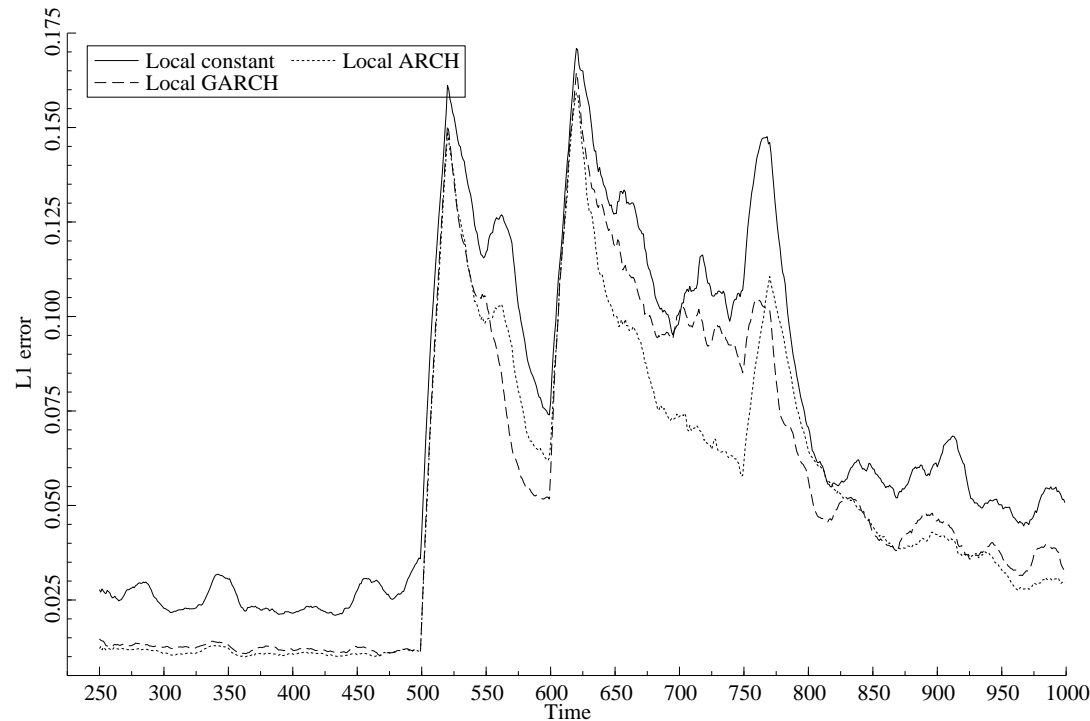
## *Submodel hierarchy*

- construct sequence of submodels  $M_0 \subset M_1 \subset \dots \subset M_S$
- search interval  $I_k$  for model  $M_k, k = 0, 1, \dots, S,$
- select best model by forecasting performance

# Simulations from change-point GARCH

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- 1000 observations, 100 replications, 1 period ahead
- Structural breaks in volatility at 500, 600, 750
- $L_1$  prediction error averaged over 20 observations
- GARCH(c,0.2,0.1): ARCH and GARCH perform equally

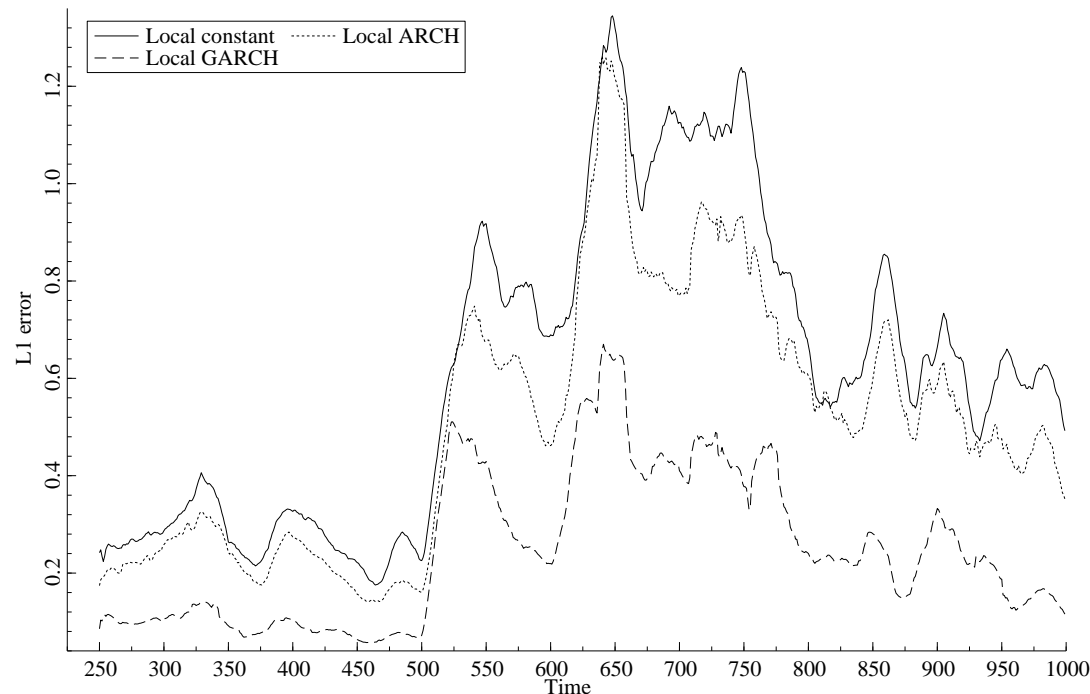


- GARCH(c,0.2,0.7): GARCH prevails (short horizon only)

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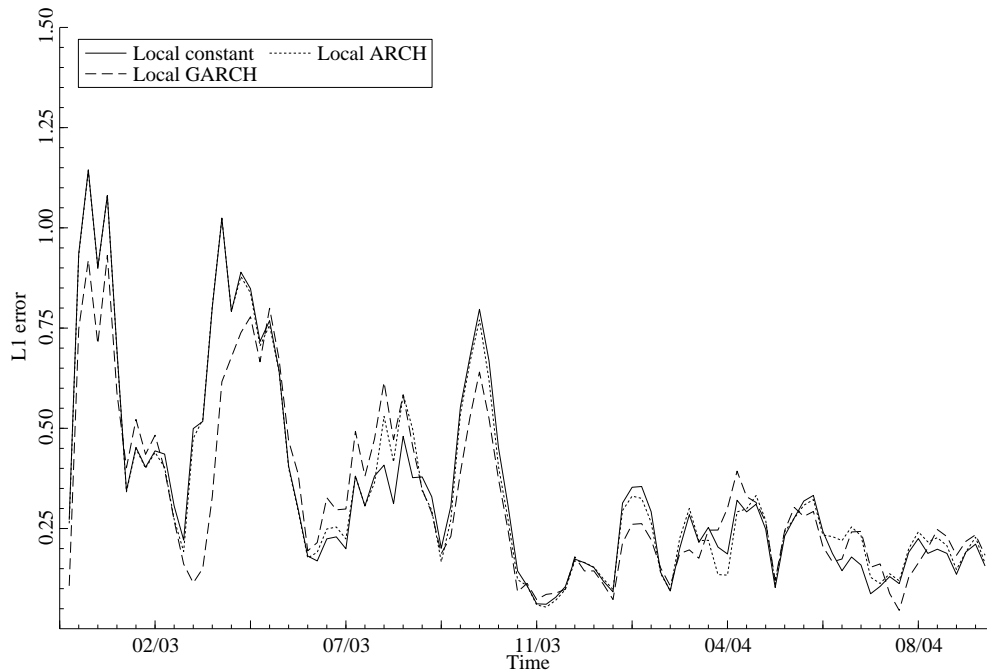
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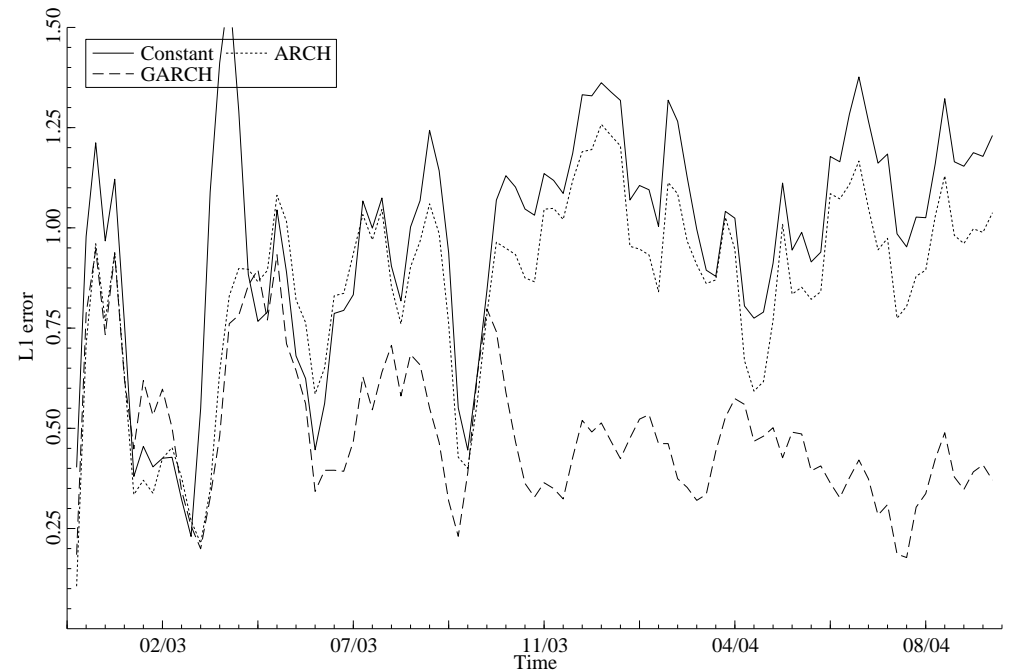
# Standard & Poors 500 index

- S&P500 stock index from January 2000 to October 2004
- Prediction horizon: one day ahead
- Prediction period: January 2003 to October 2004
- $L_1$  prediction error averaged over 20 observations (one month)

Adaptive methods



Parametric methods

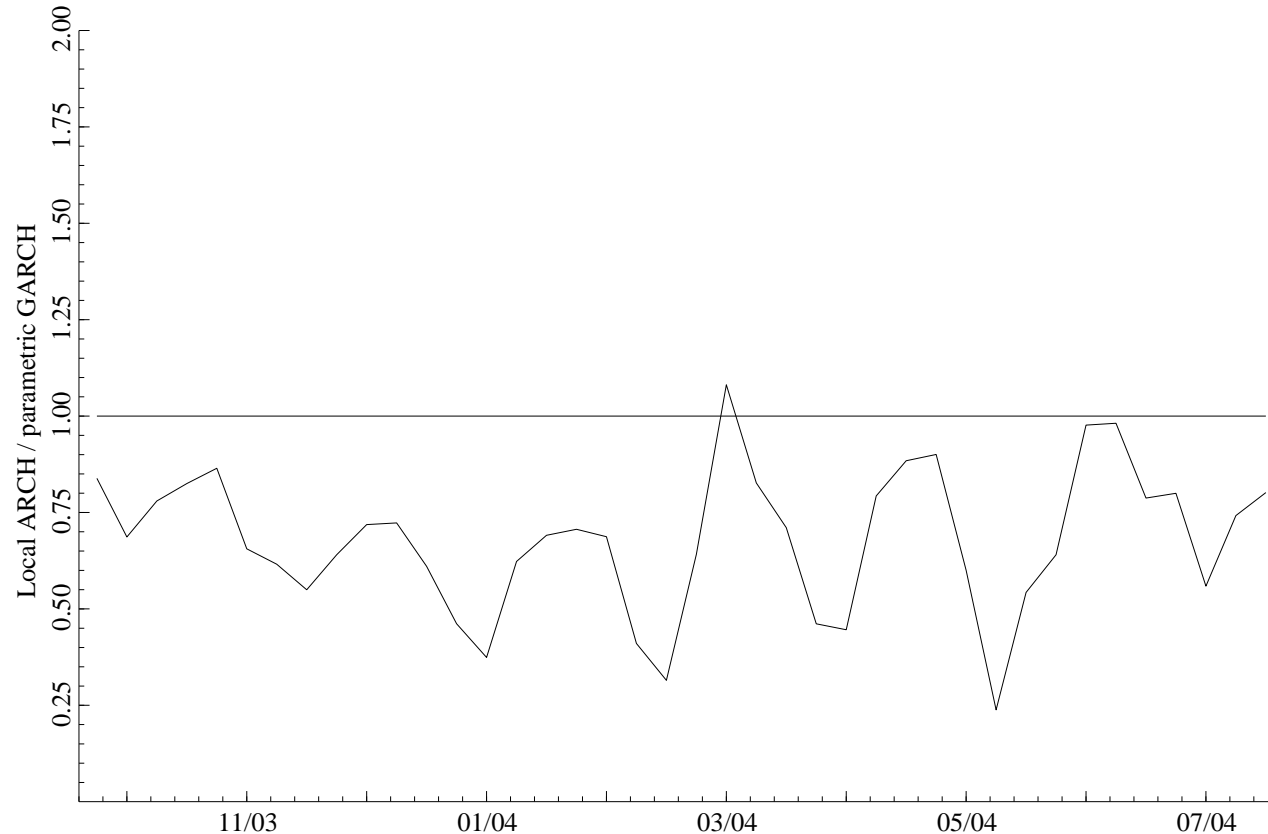




# Adaptive ARCH vs. parametric GARCH

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- S&P500 index from January 2000 to August 2004
- Prediction: one day, September 2003 to August 2004
- Ratio of  $L_1$  prediction errors: adaptive ARCH / GARCH



# Conclusion

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- Pointwise adaptive estimation for GARCH
  - search for the longest interval of homogeneity possible using a submodel hierarchy
  - detect breaks in stock index series (10/1997, 3/2003, ...)
  - outperforms standard GARCH
- Pointwise adaptive estimation for ARCH
  - can perform as well as GARCH
  - less sensitive to choice of critical values
  - other model hierarchies reasonable (e.g., ARCH(0) – ARCH(1) – ... – ARCH(p))