

Locally Adaptive Multiplicative Error Models

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Transaction Time Points

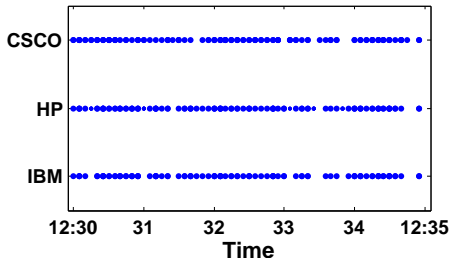


Figure 1: Buy/sell transaction time points for CSCO, HP and IBM stocks on Mai 1, 2009 from 12:30 until 12:35



Objectives

- (i) Modelling key market microstructure processes
 - ▶ Durations: time between buy/sell transactions or quotes, until price changes or until order executions
 - ▶ Relationship with stock price, bid-ask spread, trading volume

- (ii) Finding the longest time period of parameter homogeneity for a process at given time
 - ▶ Change point detection
 - ▶ Optimal buy/sell trading times

- (iii) Forecasting and financial applications



Statistical Challenges

- Financial data described by a (partially) unobserved process
- Time-varying parameters and structural breaks
- Modern nonparametric statistical techniques
- Flexible statistical framework for modelling and forecasting financial processes



Economic Implications

- Modelling trading activity for buying and selling
- Intensity of demand for and supply of liquidity
- Assessing alternative risk and volatility measures
- Time-varying market liquidity intensity
- Financial applications



Outline

1. Motivation ✓
2. Multiplicative Error Models (MEM)
3. Local Parametric Approach
4. Data
5. Modelling and Forecasting
6. Conclusions



Multiplicative Error Models (MEM)

- Proposed by Engle (2002), MEM(p, q):

$$y_t = \mu_t \varepsilon_t, \quad E[\varepsilon_t | \mathcal{F}_{t-1}] = 1 \quad (1)$$

$$\mu_t = \omega + \sum_{i=1}^p \alpha_i y_{t-i} + \sum_{j=1}^q \beta_j \mu_{t-j}, \quad \omega, \alpha_i, \beta_j \geq 0 \quad (2)$$

- y_t - squared (de-meanned) log return: GARCH(p, q) models
- y_i - financial duration: linear ACD(p, q) models



Autoregressive Conditional Duration (ACD) Models

- Linear ACD model - linear news impact function, ACD(1, 1) with $\theta^* = [\omega^*, \alpha^*, \beta^*]^\top$ and $\tilde{\theta} = \arg \max_{\theta \in \Theta} L(\theta)$:

$$\mu_i = \omega + \alpha y_{i-1} + \beta \mu_{i-1}, \quad \omega > 0, \quad \alpha, \beta \geq 0 \quad (3)$$

$$\mu_i = \omega + (\alpha \varepsilon_{i-1} + \beta) \mu_{i-1} \quad (4)$$

- (i) Exponential-ACD model (EACD) - $\varepsilon_i \sim \text{Exp}(1)$
- (ii) Weibull-ACD model (WACD) - $\varepsilon_i \sim W(1, s)$



Financial Duration Processes

- Trade and quote durations
 - ▶ Trade durations (buy and sell) - trading intensity
 - ▶ Quote durations - intensity of liquidity supply

- Price durations
 - ▶ Price durations - alternative risk and volatility measures
 - ▶ Directional change durations - optimal trading times

- Volume durations
 - ▶ Volume durations - time-varying market liquidity
 - ▶ Excess volume durations - intensity of demand for liquidity



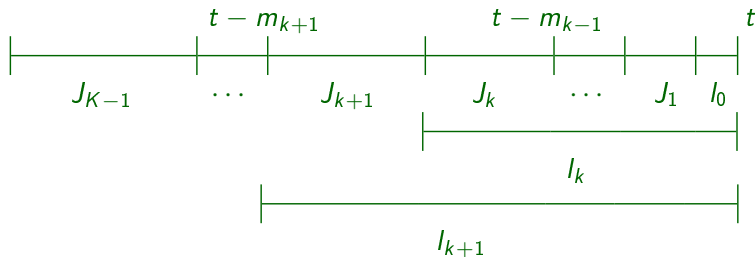
Local Parametric Approach

- Firstly proposed by Spokoiny (1998)
- Four steps for a given parametric model:
 - ◆ Risk bound, $\mathcal{R}_r(\theta^*)$
 - 📖 Propagation condition
 - 📄 Small modelling bias (SMB) condition
 - 📊 Stability and oracle property
- Algorithm:
 1. Interval selection, I_k
 2. Local change point (LCP) detection test
 3. Critical values for the LCP detection test, ξ_k

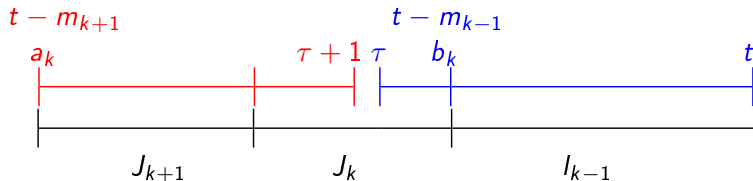


Interval Selection, I_k

- Set of intervals $\{I_k\}_{k=0}^K$, $I_0 \subset I_1 \subset \dots \subset I_K$, length $m_k = |I_k|$
- Example: fix t , $I_k = [t - m_k, t]$, $m_k = m_0 c^k$, $c > 1$



Local Change Point (LCP) Detection Test



- Hypotheses at step $k = 1, \dots, K$ and fixed t :

H_0 : y_i follows a given parametric model over $I_k = I_{k-1} \cup J_k$

H_1 : Non-consistency of the given parametric model over I_k ;
Change point within $J_k = I_k \setminus I_{k-1}$

- Test statistics and critical value

$$T_{I_k, J_k} = \sup_{\tau \in J_k} \left\{ L\left(\tilde{\theta}_{[a_k, \tau+1]}\right) + L\left(\tilde{\theta}_{[\tau, t]}\right) - L\left(\tilde{\theta}_{[a_k, t]}\right) \right\} \leq 3k \quad (5)$$



Risk Bound and Propagation Condition



Risk bound with $L(\tilde{\theta}, \theta^*) = L(\tilde{\theta}) - L(\theta^*)$ and power r

$$\mathbb{E}_{\theta^*} \left| L(\tilde{\theta}, \theta^*) \right|^r \leq \mathcal{R}_r(\theta^*) \quad (6)$$



Propagation (\mathfrak{z}_k selection): $\hat{\theta}_k$ is close to $\tilde{\theta}_k$ at step k ;
Index of the largest interval of homogeneity, \hat{k}

$$\mathbb{E}_{\theta^*} \left| L(\tilde{\theta}_k, \hat{\theta}_k) \right|^r \leq \rho_k \mathcal{R}_r(\theta^*) \quad (7)$$

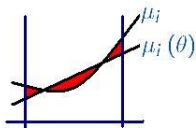
$$\hat{k} = \max_{k \leq K} \{k : T_s \leq \mathfrak{z}_s\}, \quad s = 1, \dots, k, \quad \hat{\theta}_k = \tilde{\theta}_{\hat{k}} \quad (8)$$



SMB Condition and Stability Property



SMB condition: 'true' model μ_i well approximated by $\mu_i(\theta)$



$$\Delta_{I_k}(\theta) = \sum_i \mathcal{K} \{ \mu_i, \mu_i(\theta) \} \leq \Delta \quad (9)$$



Stability property: attaining the quality of estimation

$$L_{I_{k^*}}(\tilde{\theta}_{k^*}, \hat{\theta}_{\hat{k}}) \mathbb{I} \{ \hat{k} \geq k^* \} \leq \tilde{\alpha}_k \quad (10)$$



Data

□ Data

- ▶ NYSE TAQ database, Mai 1 to July 31, 2009
Analyzing 3 stocks: CSCO, HP, IBM
- ▶ y_i : trade duration process (daily sampling period: 10:00-15:00)

Stock	\bar{y}	$\hat{\sigma}_y$	$y_{max.}$	BP_y
CSCO	2.0	1.7	40.0	60770
HP	5.6	7.8	164.0	35411
IBM	2.6	2.9	59.0	67743

Table 1: Descriptive statistics in seconds and Box-Pierce (BP) test statistics for CSCO, HP and IBM trade durations from Mai-July 2009



Estimated Parameter, $\tilde{\theta} = [\tilde{\omega}, \tilde{\alpha}, \tilde{\beta}]^T$

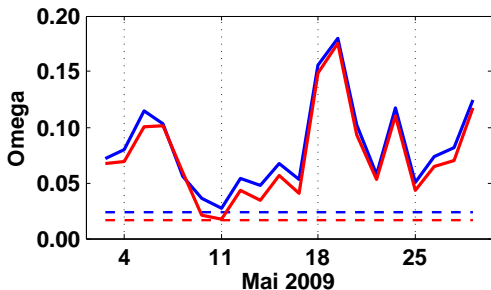


Figure 2: Estimated daily (solid) and monthly (dashed) $\tilde{\omega}$ using the **EACD(1,1)** and the **WACD(1,1)** model for IBM



Estimated Parameter, $\tilde{\theta} = [\tilde{\omega}, \tilde{\alpha}, \tilde{\beta}]^T$

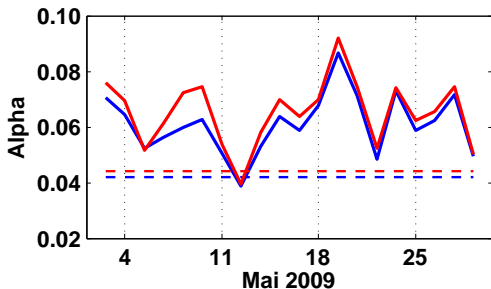


Figure 3: Estimated daily (solid) and monthly (dashed) $\tilde{\alpha}$ using the [EACD\(1,1\)](#) and the [WACD\(1,1\)](#) model for IBM



Estimated Parameter, $\tilde{\theta} = [\tilde{\omega}, \tilde{\alpha}, \tilde{\beta}]^T$

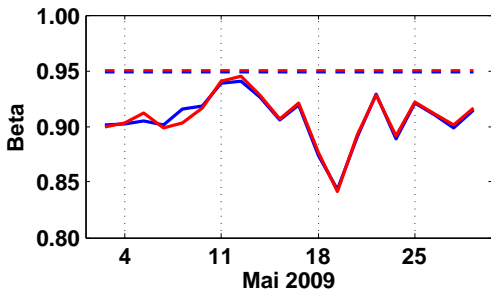


Figure 4: Estimated daily (solid) and monthly (dashed) $\tilde{\beta}$ using the $EACD(1,1)$ and the $WACD(1,1)$ model for IBM



Empirical Findings

- Trade duration processes:
 - ▶ Overdispersion
 - ▶ High persistent processes
- HP has lower trading activity than CSCO and IBM
- Time-varying parameters of EACD(1, 1) and WACD(1, 1) models: local parametric approach



Further Steps

- Implementation of the local parametric approach
 - ▶ Interval selection, I_k
 - ▶ Critical values, ζ_k
- Analysing various financial processes and models
- Key market microstructure variables
- Selection of more stocks, different time horizons
- Forecasting and financial applications



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