Modelling Round-the-Clock Price Discovery for

Cross-Listed Stocks using State Space Methods

Albert J. Menkveld   Siem-Jan Koopman   André Lucas

Vrije Universiteit Amsterdam

time line

Amsterdam

New York

	↑	↑	↑	↑	↑	↑
τ	1	2	3	4	5	6
EST	4:00	8:00	9:00	10:00	11:00	15:30

agenda

1. literature review
2. a state space approach
3. estimation and signal extraction
4. NYSE-listed Dutch stocks
5. summary

summary

We propose state space model to study round-the-clock price discovery for (partially) overlapping markets. It deals naturally with: (i) simultaneous quotes in overlap (ii) missing observations in non-overlap (iii) transient price changes due to “microstructure” effects

Findings:

- “NYSE Open” very informative, primarily stock-specific
- “NYSE Only” least informative and strong temporary effects
- overlap midquotes noisier for NYSE
- return persistence and noisy quotes for overlap indicate order-splitting
- results differ from “variance ratio” results

1. literature review

literature

(i) Price discovery in fragmented markets

- Methodology for measuring contribution to price discovery was developed for simultaneous trading (see Hasbrouck (1995), Gonzalo and Granger (1995)), Harris, McInish, and Wood (2002), J of Financial Markets 2002(3))

literature

(i) Price discovery in fragmented markets

- Methodology for measuring contribution to price discovery was developed for simultaneous trading (see Hasbrouck (1995), Gonzalo and Granger (1995)), Harris, McInish, and Wood (2002), J of Financial Markets 2002(3))
- For non-U.S. stocks cross-listed in U.S. the evidence is
  - NYSE contributes at most 30% for Dutch, German, and Spanish stocks (Hupperets and Menkveld (2002), Grammig, Melvin, and Schlag (2001), Pascual, Pascual-Fuste, and Climent (2001))
  - U.S. prices adjust more to Canadian prices than vice versa (Eun and Sabherwal (2003))

literature (cont)

(ii) Round-the-clock price discovery

- Single-market studies on 24-hour price discovery study variance ratios of open-to-close and close-to-open returns (Oldfield and Rogalski (1980), French and Roll (1986), Harvey and Huang (1991), Jones, Kaul, and Lipson (1994), and George and Hwang (2001))

literature (cont)

(ii) Round-the-clock price discovery

- Single-market studies on 24-hour price discovery study variance ratios of open-to-close and close-to-open returns (Oldfield and Rogalski (1980), French and Roll (1986), Harvey and Huang (1991), Jones, Kaul, and Lipson (1994), and George and Hwang (2001))
- Multiple-market studies "without" overlap
  1. Regress home market overnight returns on return in foreign market(s) (Craig, Dravid, and Richardson (1995))
  2. Calculate Weighted Price Contributions (WPCs) as the foreign market return divided by overnight return in home market (Barclay and Hendershott (2003), Barclay and Warner (1993))

literature (cont)

(iii) Issues that arise in applying existing methodologies for studying round-the-clock price discovery in multiple, partially overlapping markets

- prefer not to, *ex-ante*, choose a “home market”
- transient price changes due to microstructure effects
- missing observations in the non-overlap
- allow parameters to depend on time of day and market
- commonality in returns (Ronen (1997))

2. a state space approach

model

We propose a state space model, that arises naturally after

- we assume the unobserved, efficient price is characterized by a random walk

model

We propose a state space model, that arises naturally after

- we assume the unobserved, efficient price is characterized by a random walk
- we allow for non-trivial intraday seasonality in volatility

model

We propose a state space model, that arises naturally after

- we assume the unobserved, efficient price is characterized by a random walk
- we allow for non-trivial intraday seasonality in volatility
- we assume the observed midquotes equal the efficient price plus transient “microstructure” effects

model

We propose a state space model, that arises naturally after

- we assume the unobserved, efficient price is characterized by a random walk
- we allow for non-trivial intraday seasonality in volatility
- we assume the observed midquotes equal the efficient price plus transient "microstructure" effects

$$\alpha_{t,\tau} = \alpha_{t,\tau-1} + \eta_{t,\tau} \qquad \text{(state equation)}$$

model

We propose a state space model, that arises naturally after

- we assume the unobserved, efficient price is characterized by a random walk

- we allow for non-trivial intraday seasonality in volatility

- we assume the observed midquotes equal the efficient price plus transient “microstructure” effects

$$\alpha_{t,\tau} = \alpha_{t,\tau-1} + \eta_{t,\tau} \quad \text{(state equation)}$$

$$p_{k,t,\tau} = \alpha_{t,\tau} + \epsilon_{k,t,\tau} \quad \text{(observation equation market } k\text{)}$$

state equations

The (unobserved) efficient price process is defined as:

$$\underline{\alpha}_{t,\tau} = \underline{\alpha}_{t,\tau-1} + \underline{\beta}\xi_{t,\tau} + \underline{\eta}_{t,\tau}$$

$$\xi_{t,\tau} \sim \mathrm{N}(0, \sigma^2_{\xi,\tau}) \qquad \underline{\eta}_{t,\tau} \sim \mathrm{N}(\underline{\mu}_{\tau}, \sigma^2_{\eta,\tau} C)$$

with $\alpha_{t,0} = \alpha_{t-1,T}$ and C = diag(c_1,. . . ,c_n).

state equations

The (unobserved) efficient price process is defined as:

$$\underline{\alpha}_{t,\tau} = \underline{\alpha}_{t,\tau-1} + \underline{\beta}\xi_{t,\tau} + \underline{\eta}_{t,\tau}$$

$$\xi_{t,\tau} \sim \mathrm{N}(0, \sigma^2_{\xi,\tau}) \qquad \underline{\eta}_{t,\tau} \sim \mathrm{N}(\underline{\mu}_\tau, \sigma^2_{\eta,\tau} C)$$

with $\alpha_{t,0} = \alpha_{t-1,T}$ and C = diag(c_1,. . . ,c_n).

To ensure identification of the model, we impose the parameter restrictions

$$\frac{1}{n}\sum_{i=1}^{n} \beta_i^2 = 1 \qquad \frac{1}{n}\sum_{i=1}^{n} c_i = 1$$

state equations

The (unobserved) efficient price process is defined as:

$$\underline{\alpha}_{t,\tau} = \underline{\alpha}_{t,\tau-1} + \underline{\beta}\xi_{t,\tau} + \underline{\eta}_{t,\tau}$$

$$\xi_{t,\tau} \sim \mathrm{N}(0, \sigma^2_{\xi,\tau}) \qquad \underline{\eta}_{t,\tau} \sim \mathrm{N}(\underline{\mu}_{\tau}, \sigma^2_{\eta,\tau} C)$$

with $\alpha_{t,0} = \alpha_{t-1,T}$ and C = diag(c_1,...,c_n).

To ensure identification of the model, we impose the parameter restrictions

$$\frac{1}{n}\sum_{i=1}^{n} \beta_i^2 = 1 \qquad \frac{1}{n}\sum_{i=1}^{n} c_i = 1$$

Round-the-clock price discovery is then determined by

$$\sigma^2_{E,\tau} = \sigma^2_{\xi,\tau} + \sigma^2_{\eta,\tau}$$

observation equations

The observation equation for market *k* is defined as:

$$\underline{\boldsymbol{p}}_{k,t,\tau} = \underline{\boldsymbol{\alpha}}_{t,\tau} + \underline{\boldsymbol{\varepsilon}}_{k,t,\tau} \qquad \underline{\boldsymbol{\varepsilon}}_{k,t,\tau} \sim \mathrm{N}(\underline{\mathbf{0}}, \boldsymbol{\sigma}^{2}_{\varepsilon,k,\tau} \cdot \boldsymbol{I}_n)$$

observation equations

The observation equation for market *k* is defined as:

$$\underline{p}_{k,t,\tau} = \underline{\alpha}_{t,\tau} + \underline{\varepsilon}_{k,t,\tau} \qquad \underline{\varepsilon}_{k,t,\tau} \sim \mathrm{N}(\underline{0}, \sigma^2_{\varepsilon,k,\tau} \cdot I_n)$$

We extend to account for potential “lagged” market response (due to e.g. strategic trading, inventory control by liquidity suppliers):

$$\begin{aligned} \underline{p}_{k,t,\tau} &= \underline{\alpha}_{t,\tau} + \theta(\underline{\alpha}_{t,\tau} - \underline{\alpha}_{t,\tau-1}) + \underline{\varepsilon}_{k,t,\tau} \\ &= \underline{\alpha}_{t,\tau} + \theta\underline{\beta}\xi_{t,\tau} + \theta\underline{\eta}_{t,\tau} + \underline{\varepsilon}_{k,t,\tau} \end{aligned}$$

observation equations

The observation equation for market *k* is defined as:

$$\underline{p}_{k,t,\tau} = \underline{\alpha}_{t,\tau} + \underline{\varepsilon}_{k,t,\tau} \qquad \underline{\varepsilon}_{k,t,\tau} \sim \mathrm{N}(\underline{0}, \sigma^2_{\varepsilon,k,\tau} \cdot I_n)$$

We extend to account for potential “lagged” market response (due to e.g. strategic trading, inventory control by liquidity suppliers):

$$\begin{aligned}\underline{p}_{k,t,\tau} &= \underline{\alpha}_{t,\tau} + \theta(\underline{\alpha}_{t,\tau} - \underline{\alpha}_{t,\tau-1}) + \underline{\varepsilon}_{k,t,\tau} \\ &= \underline{\alpha}_{t,\tau} + \theta\underline{\beta}\xi_{t,\tau} + \theta\underline{\eta}_{t,\tau} + \underline{\varepsilon}_{k,t,\tau}\end{aligned}$$

And, we allow for time-of-day and innovation-specific θ

$$\underline{p}_{k,t,\tau} = \underline{\alpha}_{t,\tau} + \theta_{\xi,\tau}\underline{\beta}\xi_{t,\tau} + \theta_{\eta,\tau}\underline{\eta}_{t,\tau} + \underline{\varepsilon}_{k,t,\tau}$$

model

Therefore, the model we will estimate is

$$\begin{aligned}
\underline{\boldsymbol{\alpha}}_{t,\tau} &= \underline{\boldsymbol{\alpha}}_{t,\tau-1} + \underline{\boldsymbol{\beta}}\boldsymbol{\xi}_{t,\tau} + \underline{\boldsymbol{\eta}}_{t,\tau} \\
\underline{\boldsymbol{p}}_{k,t,\tau} &= \underline{\boldsymbol{\alpha}}_{t,\tau} + \boldsymbol{\theta}_{\xi,\tau}\underline{\boldsymbol{\beta}}\boldsymbol{\xi}_{t,\tau} + \boldsymbol{\theta}_{\eta,\tau}\underline{\boldsymbol{\eta}}_{t,\tau} + \underline{\boldsymbol{\varepsilon}}_{k,t,\tau}
\end{aligned}$$

with parameter vector

$$\left[\underline{\boldsymbol{\sigma}}_{\xi}^{2\prime},\ \underline{\boldsymbol{\theta}}_{\xi}',\ \underline{\boldsymbol{\sigma}}_{\eta}^{2\prime},\ \underline{\boldsymbol{\theta}}_{\eta}',\ \underline{\boldsymbol{\sigma}}_{\varepsilon,A}^{2\prime},\ \underline{\boldsymbol{\sigma}}_{\varepsilon,NY}^{2\prime},\ \underline{\boldsymbol{\beta}}',\ \underline{\boldsymbol{c}}'\right]'$$

3. estimation and signal extraction

state space representation

The standard state space model is formulated for a vector of observations $\boldsymbol{y_s}$ with a single time index $\boldsymbol{s}$:

$$
\begin{aligned}
\boldsymbol{\delta_{s+1}} &= \boldsymbol{T_s \delta_s + R_s \chi_s} && \text{(state equation)} \\
\boldsymbol{y_s} &= \boldsymbol{Z_s \delta_s + \nu_s} && \text{(observation equation)}
\end{aligned}
$$

for $\boldsymbol{s = 1}$,...,$\boldsymbol{M}$ and disturbances $\boldsymbol{\chi_s \sim \mathrm{N}(0, Q_s)}$ and $\boldsymbol{\nu_s \sim \mathrm{N}(0, H_s)}$ are mutually and serially uncorrelated. The initial state vector $\boldsymbol{\delta_1 \sim \mathrm{N}(a, P)}$ is uncorrelated with the disturbances. The system matrices or vectors $\boldsymbol{Z_s}$, $\boldsymbol{T_s}$, $\boldsymbol{R_s}$, $\boldsymbol{H_s}$ and $\boldsymbol{Q_s}$, together with the initial mean $\boldsymbol{a}$ and variance $\boldsymbol{P}$, are assumed as fixed and known for all $\boldsymbol{s}$. This general state space model is explored further in textbooks of Harvey (1989) and Durbin and Koopman (2001), amongst others.

state space representation (cont)

Our model can be represented as a state space model by choosing:

$$y_s = \left(p'_{1,t,\tau}, \ldots, p'_{K,t,\tau}\right)' \qquad \delta_s = \left(\alpha'_{t,\tau}, \eta'_{t,\tau-1}, \xi_{t,\tau-1}\right)'$$

$$\chi_s = \left(\eta'_{t,\tau}, \xi_{t,\tau}\right)' \qquad s = (t-1)\cdot T + \tau$$

The state space matrices are

$$Z_s = \iota_K \otimes [I_n, \theta_{\eta,\tau} I_n, \theta_{\xi,\tau}\beta]$$

$$T_s = \begin{bmatrix} I_n & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad R_s = \begin{bmatrix} I_n & \beta \\ I_n & 0 \\ 0 & 1 \end{bmatrix} \quad Q_s = \begin{bmatrix} \sigma^2_{\eta,\tau} C & 0 \\ 0 & \sigma^2_{\xi,\tau} \end{bmatrix}$$

estimation and signal extraction

The Kalman filter evaluates the conditional mean and variance of the state vector $\boldsymbol{\delta_s}$ given the past observations, that is

$$\boldsymbol{a_{s|s-1}} = \mathsf{E}(\boldsymbol{\delta_s}|\boldsymbol{Y_{s-1}}) \qquad \boldsymbol{P_{s|s-1}} = \mathsf{var}(\boldsymbol{\delta_s}|\boldsymbol{Y_{s-1}}) \qquad \boldsymbol{s} = 1, \ldots, \boldsymbol{M}$$

where $\boldsymbol{a_{1|Y_0}} = \boldsymbol{a}$ and $\boldsymbol{P_{1|Y_0}} = \boldsymbol{P}$.

estimation and signal extraction

The Kalman filter evaluates the conditional mean and variance of the state vector $\boldsymbol{\delta}_s$ given the past observations, that is

$$\boldsymbol{a}_{s|s-1} = \mathsf{E}(\boldsymbol{\delta}_s|\boldsymbol{Y}_{s-1}) \qquad \boldsymbol{P}_{s|s-1} = \mathsf{var}(\boldsymbol{\delta}_s|\boldsymbol{Y}_{s-1}) \qquad s = 1, \ldots, M$$

where $\boldsymbol{a}_{1|\mathbf{Y}_0} = \boldsymbol{a}$ and $\boldsymbol{P}_{1|\mathbf{Y}_0} = \boldsymbol{P}$.

The recursive equations are given by

$$\boldsymbol{a}_{s+1|s} = \boldsymbol{T}_s \boldsymbol{a}_{s|s-1} + \boldsymbol{K}_s \boldsymbol{v}_s$$

$$\boldsymbol{P}_{s+1|s} = \boldsymbol{T}_s \boldsymbol{P}_{s|s-1} \boldsymbol{T}_s' + \boldsymbol{R}_s \boldsymbol{Q}_s \boldsymbol{R}_s' - \boldsymbol{K}_s \boldsymbol{F}_s^{-1} \boldsymbol{K}_s'$$

with one-step ahead prediction error vector $\boldsymbol{v}_s = \boldsymbol{y}_s - \boldsymbol{Z}_s \boldsymbol{a}_{s|s-1}$, its variance matrix $\boldsymbol{F}_s = \boldsymbol{Z}_s \boldsymbol{P}_{s|s-1} \boldsymbol{Z}_s' + \boldsymbol{H}_s$ and Kalman gain matrix $\boldsymbol{K}_s = \boldsymbol{T}_s \boldsymbol{P}_{s|s-1} \boldsymbol{Z}_s' \boldsymbol{F}_s^{-1}$ for $s = 1, \ldots, M$.

estimation and signal extraction (cont)

- The parameters in the state space model are estimated by maximizing the loglikelihood that can be evaluated by the Kalman filter as a result of the prediction error decomposition. The loglikelihood function is given by

$$logL = -\frac{nKM}{2}\log 2\pi - \frac{1}{2}\sum_{s=1}^{M}\log|F_s| - \frac{1}{2}\sum_{s=1}^{M} v_s' F_s^{-1} v_s$$

- Estimation was done in **Ox** (see Doornik (2001)) using the SsfPack state space routines (see Koopman, Shephard, and Doornik (1999), **www.ssfpack.com**).

- We use the quasi-Newton method by Broyden, Fletcher, Goldfarb, and Shanno (BFGS) for the optimization of the loglikelihood.

estimation and signal extraction (cont)

- An important feature of state space methods is their ability to deal with missing values, when all elements in $\boldsymbol{y_s}$ are missing, the recursive equation reduces to

$$\boldsymbol{a}_{s+1|s} = \boldsymbol{T_s a}_{s|s-1} + \cancel{\boldsymbol{K_s v_s}}$$

$$\boldsymbol{P}_{s+1|s} = \boldsymbol{T_s P}_{s|s-1}\boldsymbol{T}_s' + \boldsymbol{R_s Q_s R}_s' - \cancel{\boldsymbol{K_s F}_s^{-1}\boldsymbol{K}_s'}$$

- Signal extraction refers to the estimation of the unobserved efficient price given all observations $\boldsymbol{Y_M}$. The conditional mean vector $\hat{\boldsymbol{\delta}}_s = \mathrm{E}(\boldsymbol{\delta}_s|\boldsymbol{Y_M})$ and conditional variance matrix $\boldsymbol{V_s} = \mathbf{var}(\boldsymbol{\delta}_s|\boldsymbol{Y_M})$ can be computed by a smoothing algorithm.

4. NYSE-listed Dutch stocks

data

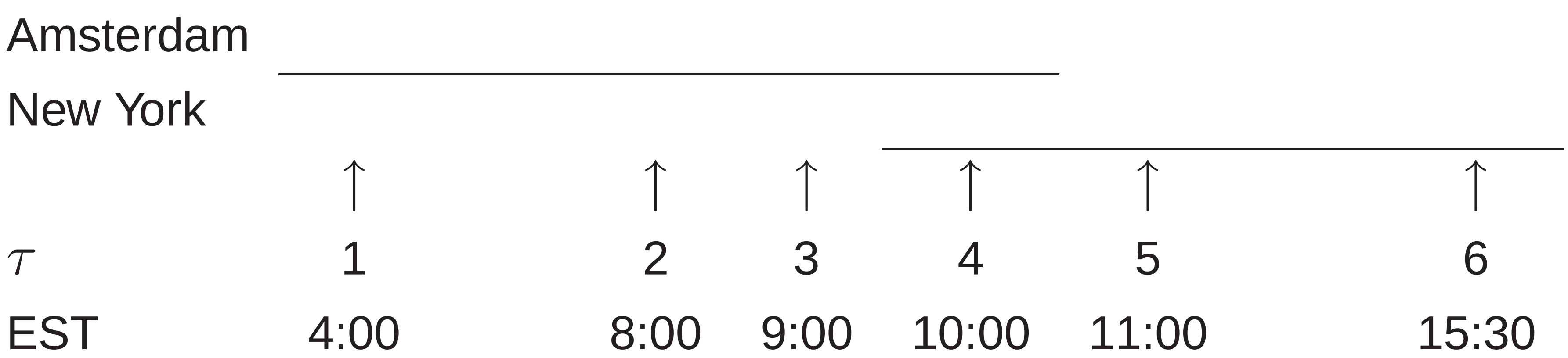
Dataset consists of

- NYSE TAQ data
- Euronext-Amsterdam trades and quotes
- Olsen&Associates exchange rate quotes

for

- July 1997 through June 1998
- seven Dutch stocks: Aegon, Ahold, KLM, KPN, Philips, Royal Dutch, Unilever

time line



time line

Amsterdam						
New York						
	↑	↑	↑	↑	↑	↑
τ	1	2	3	4	5	6
EST	4:00	8:00	9:00	10:00	11:00	15:30

Time points far apart to ensure independence of transient effects.

Hansen and Lunde (2004, p. 2): *“In fact, our empirical analysis shows that the noise process has a time-dependence that persists for up to about two minutes.”*

the model

To recap, the model we will estimate is

$$
\begin{aligned}
\underline{\boldsymbol{\alpha}}_{t,\tau} &= \underline{\boldsymbol{\alpha}}_{t,\tau-1} + \underline{\boldsymbol{\beta}}\boldsymbol{\xi}_{t,\tau} + \underline{\boldsymbol{\eta}}_{t,\tau} \\
\underline{\boldsymbol{p}}_{k,t,\tau} &= \underline{\boldsymbol{\alpha}}_{t,\tau} + \boldsymbol{\theta}_{\xi,\tau}\underline{\boldsymbol{\beta}}\boldsymbol{\xi}_{t,\tau} + \boldsymbol{\theta}_{\eta,\tau}\underline{\boldsymbol{\eta}}_{t,\tau} + \underline{\boldsymbol{\varepsilon}}_{k,t,\tau}
\end{aligned}
$$

with parameter vector

$$
\left[\underline{\boldsymbol{\sigma}}'_{\xi},\ \underline{\boldsymbol{\theta}}'_{\xi},\ \underline{\boldsymbol{\sigma}}'_{\eta},\ \underline{\boldsymbol{\theta}}'_{\eta},\ \underline{\boldsymbol{\sigma}}'_{\varepsilon,A},\ \underline{\boldsymbol{\sigma}}'_{\varepsilon,NY},\ \underline{\boldsymbol{\beta}}',\ \underline{\boldsymbol{c}}'\right]'
$$

with sample length 220*6=1320, state vector dimension 7+7+1=15, observation vector dimension 2*7=14, number of parameters 6+6+6+6+4+3+7+7=45

4:00−8:00
AMS Only

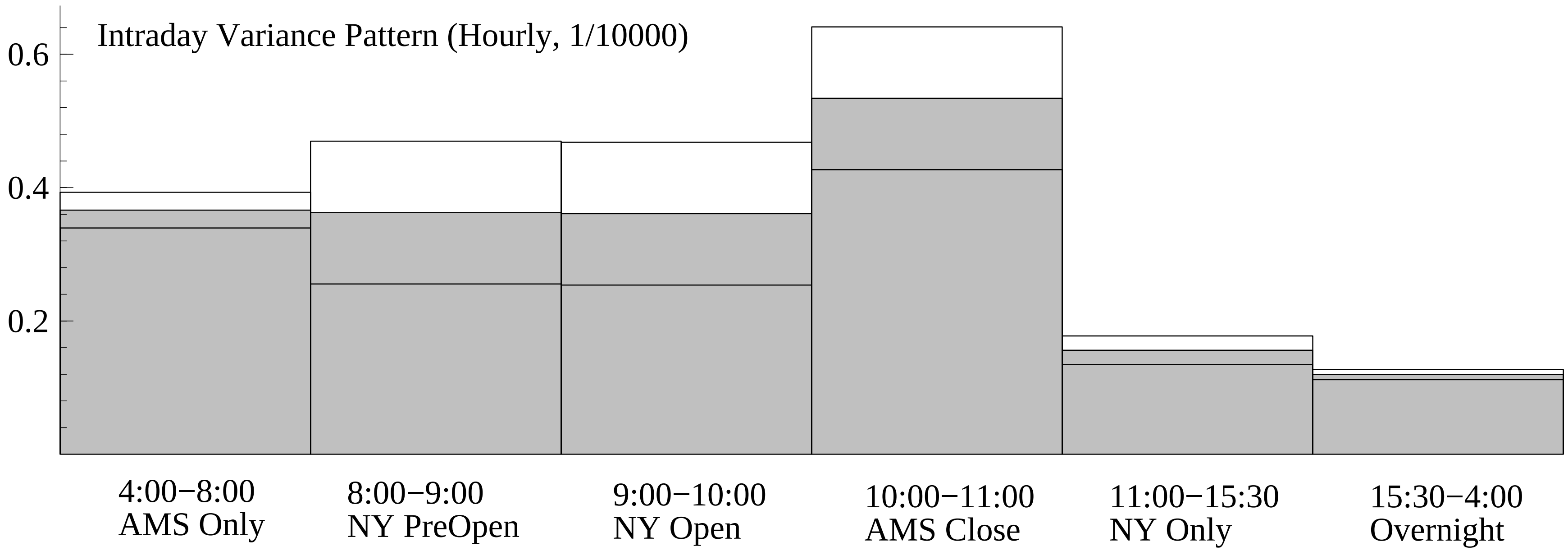
8:00−9:00
NY PreOpen

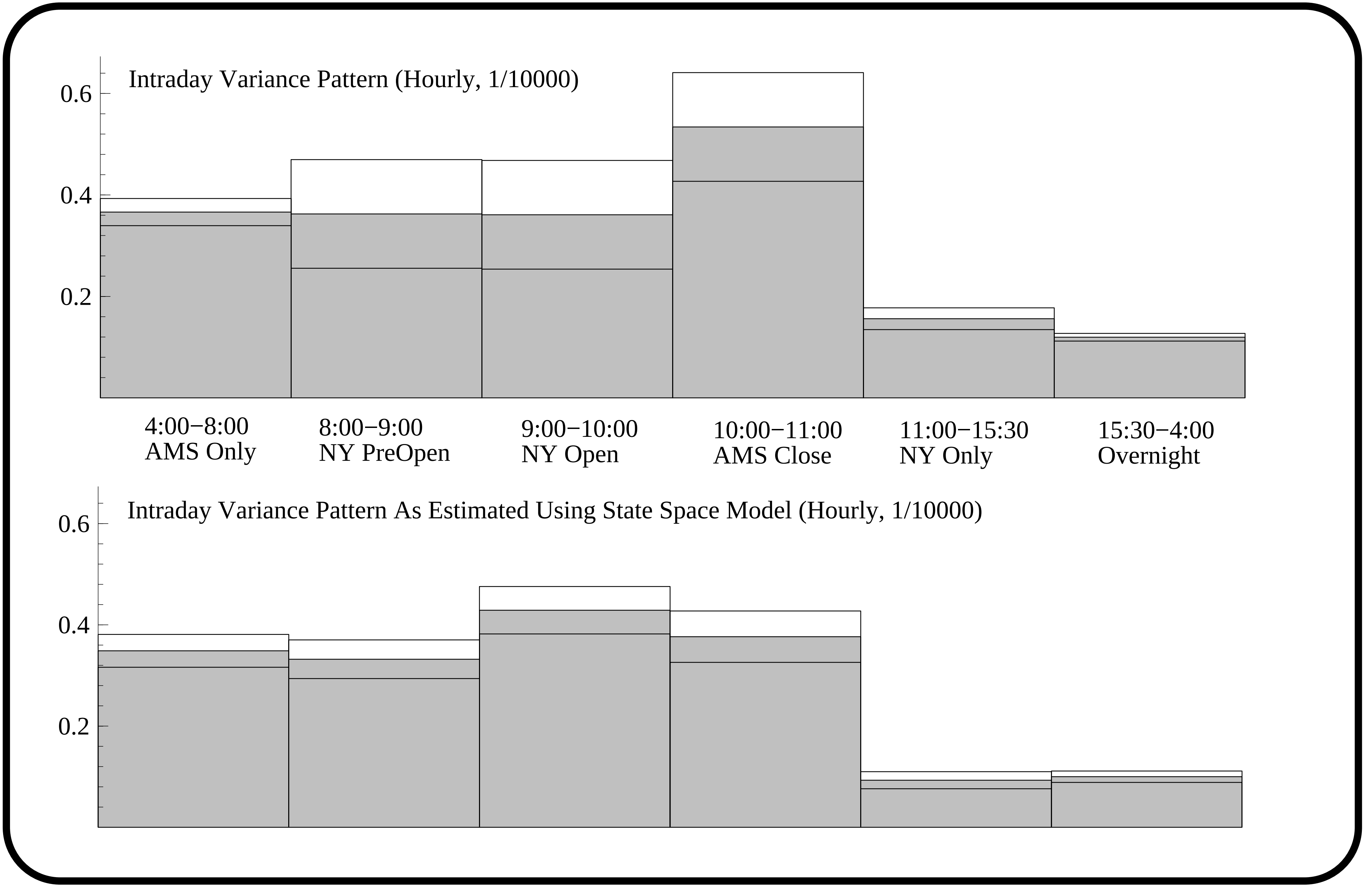
9:00−10:00
NY Open

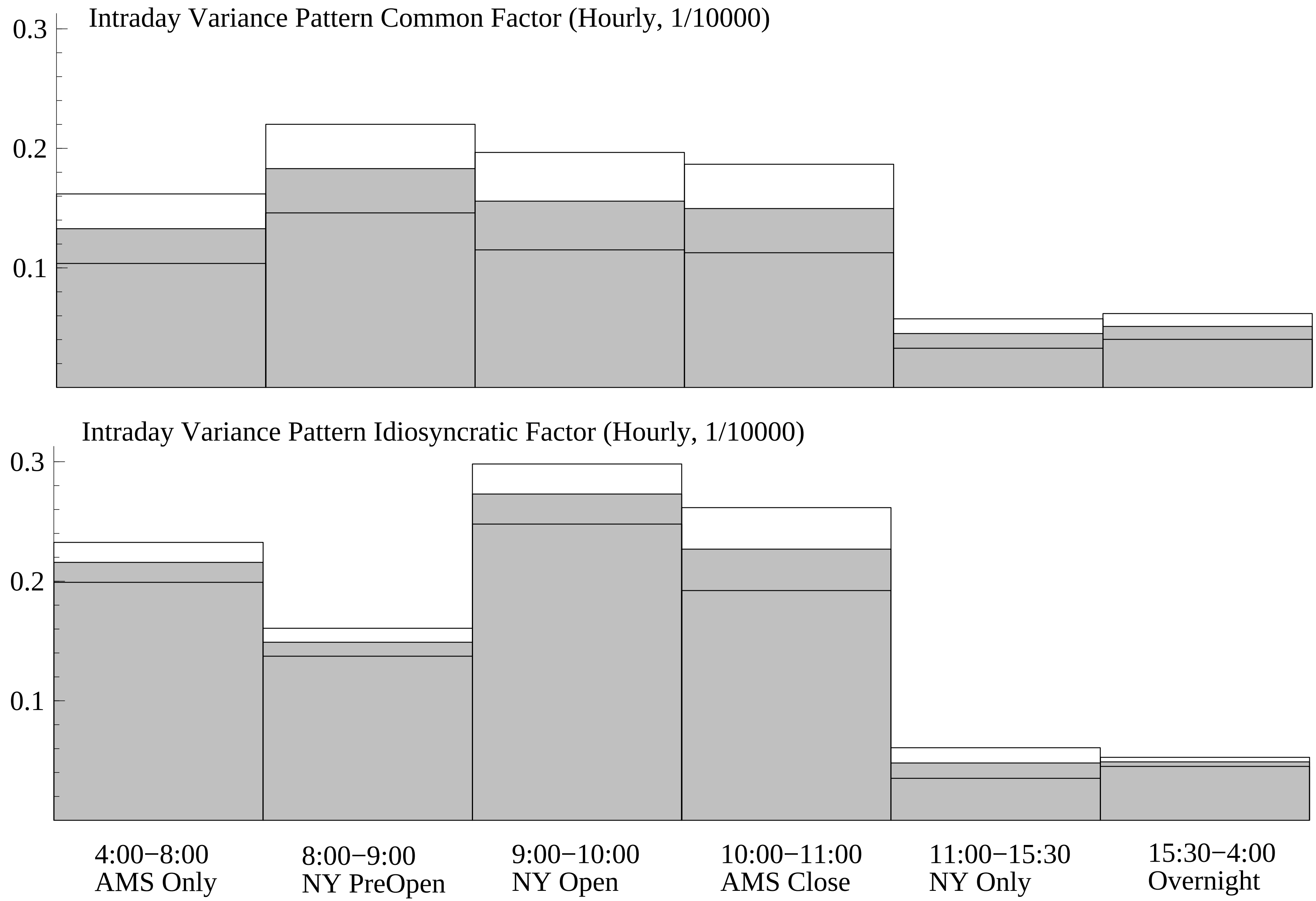
10:00−11:00
AMS Close

11:00−15:30
NY Only

15:30−4:00
Overnight


Intraday Variance Pattern (Hourly, 1/10000)
0.6
0.4
0.2
4:00−8:00
AMS Only
8:00−9:00
NY PreOpen
9:00−10:00
NY Open
10:00−11:00
AMS Close
11:00−15:30
NY Only
15:30−4:00
Overnight


Intraday Variance Pattern (Hourly, 1/10000)
0.6
0.4
0.2
4:00−8:00
AMS Only
8:00−9:00
NY PreOpen
9:00−10:00
NY Open
10:00−11:00
AMS Close
11:00−15:30
NY Only
15:30−4:00
Overnight
Intraday Variance Pattern As Estimated Using State Space Model (Hourly, 1/10000)
0.6
0.4
0.2


Intraday Variance Pattern Common Factor (Hourly, 1/10000)
0.3
0.2
0.1
Intraday Variance Pattern Idiosyncratic Factor (Hourly, 1/10000)
0.3
0.2
0.1
4:00−8:00
AMS Only
8:00−9:00
NY PreOpen
9:00−10:00
NY Open
10:00−11:00
AMS Close
11:00−15:30
NY Only
15:30−4:00
Overnight

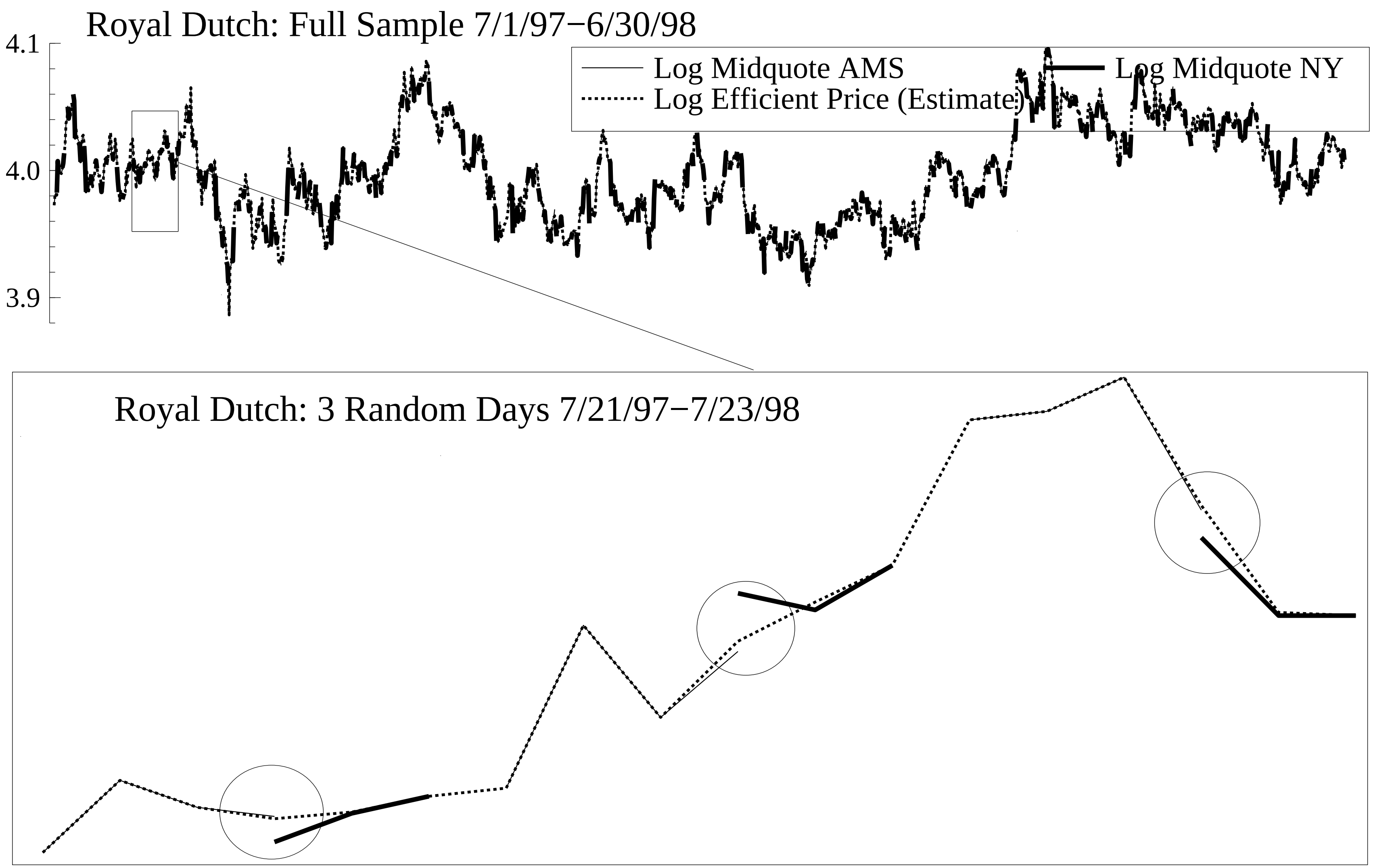
state innovations

Event	Start AMS	NY PreOpen	NY Open	AMS Close	NY Only	Over-night
Start (EST)	4:00	8:00	9:00	10:00	11:00	15:30
End	8:00	9:00	10:00	11:00	15:30	4:00
$\sigma^2_{\xi,\tau}$	0.13	0.18	0.16	0.15	0.05	0.05
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
$\theta_{\xi,\tau}$			-0.35		-0.16	
			(0.04)		(0.04)	
$\sigma^2_{\eta,\tau}$	0.22	0.15	0.27	0.23	0.05	0.05
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.00)
$\theta_{\eta,\tau}$			-0.34	-0.30	0.87	
			(0.02)	(0.08)	(0.13)	

measurement errors

	4:00	8:00	9:00	10:00	11:00	15:30
$(\sigma_\tau^{\epsilon,A})^2$	0.00	0.00	0.00	0.07		
	(0.00)	(0.00)	(0.00)	(0.01)		
$(\sigma_\tau^{\epsilon,NY})^2$				0.11	0.07	0.14
				(0.01)	(0.02)	(0.00)

efficient price estimates



correlation common factor and index

Event	Start AMS	NY PreOpen	NY Open	AMS Close	NY Only
Start (EST)	4:00	8:00	9:00	10:00	11:00
End	8:00	9:00	10:00	11:00	15:30
ρ(Common Factor, AEX)					
ρ(Common Factor, S&P500)					

correlation common factor and index

Event	Start AMS	NY PreOpen	NY Open	AMS Close	NY Only
Start (EST)	4:00	8:00	9:00	10:00	11:00
End	8:00	9:00	10:00	11:00	15:30
ρ(Common Factor, AEX)	0.57	0.38	0.08		
	(0.07)	(0.07)	(0.07)		
ρ(Common Factor, S&P500)				0.21	0.28
				(0.07)	(0.07)

robustness

We performed several robustness checks:

- sub-periods
- stock-specific measurement error variances
- correlated price innovations and measurement errors (see, e.g, George and Hwang (2001))

Results available from corresponding author’s website

5. summary

summary

We propose state space model to study round-the-clock price discovery for (partially) overlapping markets. It deals naturally with: (i) simultaneous quotes in overlap (ii) missing observations in non-overlap (iii) transient price changes due to "microstructure" effects

Findings:

- "NYSE Open" very informative, primarily stock-specific
- "NYSE Only" least informative and strong temporary effects
- overlap midquotes noisier for NYSE
- return persistence and noisy quotes for overlap indicate order-splitting
- results differ from "variance ratio" results

intraday return autocorrelations

Time Interval	Event	Lag 1	Lag 2
4:00-8:00	AMS Only	-0.077	
8:00-9:00	NY PreOpen	0.056	-0.020
9:00-10:00	NY Open	-0.125*	-0.005
10:00-11:00	AMS Close	0.251*	-0.170*
11:00-15:30	NY Only	-0.050	0.039
15:30-4:00(+1)	Overnight	-0.165*	-0.022

*: Significant at a 95% confidence level.

References

Barclay, M.J., and T. Hendershott. 2003. "Price Discovery and After Trading Hours." *Review of Financial Studies* 16(4):1041–1073.

Barclay, M.J., and J.B. Warner. 1993. "Stealth Trading and Volatility: Which Trade Moves Prices?" *Journal of Financial Economics* 34:281–305.

Craig, A., A. Dravid, and M. Richardson. 1995. "Market Efficiency around the Clock: Some Supporting Evidence using Foreign-Based Derivatives." *Journal of Financial Economics* 39:161–180.

Doornik, J.A. 2001. *Object-Oriented Matrix Programming using Ox 3.0*. London: Timberlake Consultants Press.

Durbin, J., and S.J. Koopman. 2001. *Time Series Analysis by State Space Models*. Oxford: Oxford University Press.

Eun, C.S., and S. Sabherwal. 2003. "Cross-Border Listings and Price Discovery: Evidence from U.S. Listed Canadian Stocks." *Journal of Finance* 58 (2): 549–576.

French, K., and R. Roll. 1986. "Stock Return Variances, the Arrival of Information and the Reaction of Traders." *Journal of Financial Economics* 17:5–26.

George, T.J., and C.Y. Hwang. 2001. "Information Flow and Pricing Errors: A Unified Approach to Estimation and Testing." *Review of Financial Studies* 14 (4): 979–1020.

Gonzalo, J., and C.W.J. Granger. 1995. "Estimation of Common Long-Memory Components in Cointegrated Systems." *Journal of Business and Economic Statistics* 13(1):27–36.

Grammig, J., M. Melvin, and C. Schlag. 2001. "Price Discovery in International Equity Trading." Technical Report 78, Johann Wolfgang Goethe-Universität, Frankfurt am Main.

Hansen, P.R., and A. Lunde. 2004. "An Unbiased Measure of Realized Variance." Technical Report, Stanford University.

Harris, F.H.deB., T.H. McInish, and R.A. Wood. 2002. "Security Price Adjustment across Exchanges: an Investigation of Common Factor Components for Dow stocks." *Journal of Financial Markets* 5(3):277–308.

Harvey, A.C. 1989. *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge: Cambridge University Press.

Harvey, C., and R.D. Huang. 1991. "Volatility in Foreign Currency Futures Markets." *Review of Financial Studies* 4:543–569.

Hasbrouck, J. 1995. "One Security, Many Markets: Determining the Contributions to Price Discovery." *Journal of Finance* 50:1175–1199.

Hupperets, E., and A.J. Menkveld. 2002. "Intraday Analysis of Market Integration: Dutch Blue Chips Traded in Amsterdam and New York." *Journal of Financial Markets* 5 (1): 57–82.

Jones, C.M., G. Kaul, and M.L. Lipson. 1994. "Information, Trading, and Volatility." *Journal of Financial Economics* 36:127–153.

Koopman, S.J., N. Shephard, and J.A. Doornik. 1999. "Statistical Algorithms for Models in State Space using Ssfpack 2.2." *Econometrics Journal* 2:113–166.

Oldfield, G.S., and R.J. Rogalski. 1980. "A Theory of Common Stock Returns over Trading and Non-Trading Periods." *Journal of Finance* 35:729–751.

Pascual, R., B. Pascual-Fuste, and F. Climent. 2001. “Cross-Listing, Price Discovery, and the Informativeness of the Trading Process.” Technical Report 01-45, Universidad Carlos III de Madrid.

Ronen, T. 1997. “Tests and Properties of Variance Ratios in Microstructure Studies.” *Journal of Financial and Quantitative Analysis* 32 (2): 183–203.