Volatility Spillovers in South East Asia Financial Markets

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Why a MEM?

Modeling non-negative time series

- A lot of information available in financial markets is positive valued:
  - ultra-high frequency data (within a time interval: range, volume, number of trades, number of buys/sells, durations)
  - daily volatility estimators (realized volatility, daily range, absolute returns)
- Time series exhibit persistence: GARCH–type models

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What is a Multiplicative Error Model?

A MEM for x_t (non–negative univariate process) is defined as

$$x_t = \mu_t \varepsilon_t.$$

Conditionally on $\mathcal{F}_{t-1}$:

- μ_t is a nonnegative *predictable* process function of a vector of unknown parameters θ. Example:

$$\mu_t = \omega + \alpha x_{t-1} + \beta \mu_{t-1} + \gamma x_{t-1}^{(-)}$$

- ε_t is a iid multiplicative error term

$$\varepsilon_t | \mathcal{F}_{t-1} \sim (1, \sigma^2)$$

Remark: no need to resort to logs.

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The Multiplicative Error Model

From the definition:

$$E(x_t|\mathcal{F}_{t-1}) = \mu_t$$
$$V(x_t|\mathcal{F}_{t-1}) = \sigma^2\mu_t^2$$

Why a vMEM?

Modeling interactions among non-negative time series

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Modeling interactions among non-negative time series

Example (Volatility Forecasting)

Question: What are the dynamic interactions among different measures of volatility?

vMEM answer: Build an interdependent model where realized, Bipower, Two-Scale, Daily Range, Absolute Returns can be engaged in a horse race. Inspect whether there exists a measure depending just on its own past.

Why a vMEM?

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Example (Volatility Spillovers)

Question: What are the dynamic interactions among volatilities in different market indices?
MEM answer: Build a vMEM where one can use a volatility proxy (e.g. daily range) for different markets and analyze interactions (model selection), build interdependent forecasts, derive nonlinear impulse response functions as a scenario analysis tool.

Why a vMEM?

Modeling interactions among non-negative time series

Example (Order Execution Dynamics)

Question: What is the distribution of the quantity of stock that will execute in the next time period at a given distance from the current price? Is there an interaction between such quantities?
MEM answer: Build a vMEM for execution depths. Forecasts can be used for a trading strategy (Noss, 2007).
Remark: zeros in the data are relevant because there are times when the quantity which could be executed at a certain distance from current price can be zero.

The Issues

- Financial markets characterized by increasing degrees of integration
- Integration in a given area may manifest itself in different fashions:
  - one market transmits movements to other markets, being largely unaffected by them
  - markets are interdependent, so that movements originating in one diffuse to others and through dynamic links back to the origin, or they respond in a similar fashion to outside shocks, or
  - there is independence across markets.

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The Strategy in our Paper

Motivation: empirical question $\rightarrow$ establish structure of links across markets

- start from estimation over a long period
- verify whether possible crises affect the stability of the relationships
- verify the forecasting capability of a model
- trace the effects of one shock in one market to all markets

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The Approach

- Adapt the Multiple Indicator Model for volatility dynamics (Engle and Gallo, 2006) to analyze the interdependence and dynamic transmission mechanisms of volatility across markets (South-East Asia)
- MEM describes the conditional expectation (future mean on the basis of information available) of a volatility proxy (daily range)
- Its dynamics follows a GARCH-type autoregressive structure: observations on daily range are affected also by an unpredictable innovation term with a unit mean.
- Rich dynamics: here we let past daily ranges of other markets affect the dynamics in one market.
- Potentially, we could extend it also to terms accounting for asymmetric impact of bad news on each market.

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In the empirical literature

Closest: Diebold and Yilmaz (2009); Dungey and Martin (2007)
Attention is devoted mainly to crises identified ex post.
Four groups of models (survey Pericoli and Sbracia, 2003):

- Probit/Logit models to explain crisis dichotomous variable (Eichengreen et al., 1996; Caramazza et al., 2000; Van Rijckeghem and Weder,2001) and predictive ability of leading indicators linked to economic fundamentals (Kaminsky, 1999; Kaminsky et al., 1998; Hardy, Pazarbaşoĝlu,1998)
- GARCH models for volatility spillovers (Engle et al., 1990; Fleming, Lopez, 1999, Edwards, 1998)
- Changes in correlation (Baig and Goldfajn, 1999, Forbes, Rigobon, 2002, Diebold, Yilmaz, 2007).
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Our Contribution

- We focus on volatility directly modelling its conditional expectation rather than considering financial returns and building second moments
- We collect information about relationships across volatilities not through analysis of correlations but through the analysis of how volatilities in one market (dynamically) affect expected volatilities in other markets
- We perform forecasting exercises over medium horizons (4 to 6 months)
- We trace the effect of a shock to one market to other markets (time-dependent profile)
- We build an indicator of the relative importance of the markets

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The Results

- The presence of spillovers among markets gets strong empirical support.
- Some markets present stable links across periods (HK, SI, TH)
- Other have differentiated responses in the 1997-98 crisis
  - Some have just a level shift in the constant term (MA, PH)
  - Other have also additional links during the crisis (IN, KO, TA)
- The empirical results on model dynamics confirm the leading role of HK (higher effects on other markets)
- Baht crisis (July 2, 97) has little spillover effects
- HK crisis (Oct. 22, 97) has strong effects
- Sep. 11, 2001 as a common shock has delayed and limited effects

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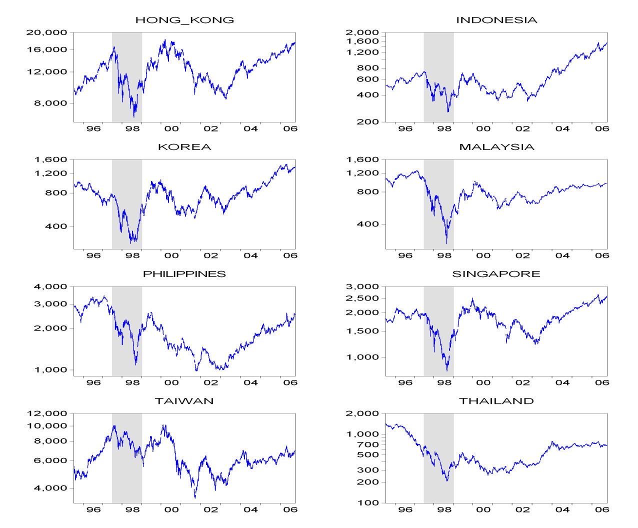
Time Series of All Indices – Jul. 1995/Oct. 2006



Volatility: Daily Range

We consider 8 markets: Hong Kong (HK), Indonesia (IN), South Korea (KO), Malaysia (MA), Philippines (PH), Singapore (SI), Taiwan (TA), Thailand (TH)

Consider daily range $hl_{i,t}$ for market i as the volatility proxy

$$hl_{i,t} = \sqrt{\frac{\pi}{8}} \log(\mathrm{high}_{i,t}) - \log(\mathrm{low}_{i,t}),$$

Period of observation: July, 14, 1995 – October, 10, 2006 (2754 obs)

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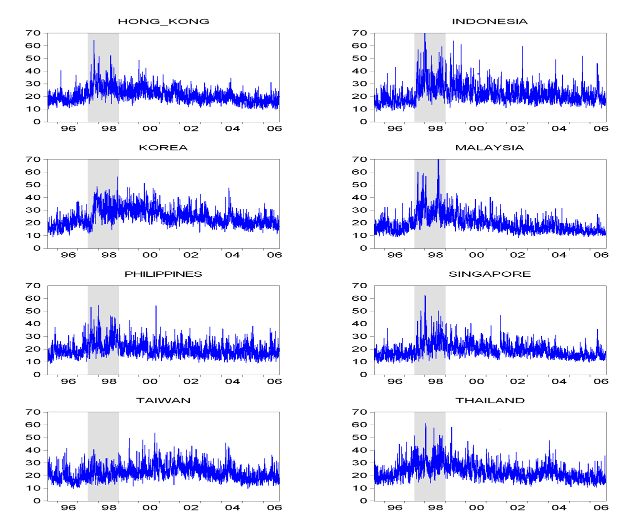
Daily Range (All Markets) – Jul. 1995/Oct. 2006



Shaded area between July 2, 1997 and Dec. 31, 1998. Truncated vertical axis leaves out one value for Indonesia (78.915) and one for Malaysia (92.27)

Descriptive Stats on Daily Range

	HK	IN	KO	MA	PH	SI	TA	TH
Mean								
Whole period	15.63	18.00	21.36	14.37	13.94	13.35	17.24	18.99
Pre–crisis	11.77	9.90	13.76	10.04	11.81	8.82	12.95	16.73
Crisis	27.55	31.39	30.54	33.08	22.71	23.18	16.46	30.85
Post–crisis	14.28	17.43	21.48	11.83	12.77	12.58	18.46	17.25
Min	2.84	2.18	2.50	2.20	2.34	2.34	2.95	3.58
Max	136.52	204.20	104.51	279.13	98.63	128.87	94.52	122.63
St.Dev	10.13	14.19	12.53	14.31	9.26	9.68	9.84	12.35
Skewness	2.78	3.38	1.45	6.01	2.73	3.47	1.72	2.52
Kurtosis	18.84	24.41	5.56	74.04	16.14	25.62	7.81	14.20
St.Dev. Returns	26.39	27.68	32.77	25.03	26.15	21.98	25.59	28.90

The MEM Base Model

Assume that, for market i

$$hl_{i,t}|I_{t-1} = \mu_{i,t} \cdot \epsilon_{i,t},$$

where $\epsilon_{i,t}|I_{t-1} \sim Gamma(\phi_i, 1/\phi_i)$ and $\mu_{i,t}$ is the conditional expectation of $hl_{i,t}$.
Simplest specification: base MEM$(1,1)$ (or a MEM(2,1))

$$\mu_{i,t} = \omega_i + \beta_i \mu_{i,t-1} + \alpha_{i,i} hl_{i,t-1} (+\psi_i hl_{i,t-2}).$$

If we considered a MEM on $r_t^2 = h_t\, \epsilon_t$, $E(r_t^2) = h_t$ modeled as a GARCH.

The MEM Extended Specification

Additional terms

1. lagged daily ranges observed in other markets to link together different markets $hl_{j,t-1},\ j \neq i$;
2. time dummies for turbulence periods. Crisis dummy: DC_t (Jul. 1, 1997- Dec. 31, 1998) Post-crisis dummy PC_t (from Jan. 1, 1999 on);
3. interaction terms between 1. and DC_{t-1} to accommodate the possibility that links change their features during the crisis;
4. own asymmetric effects for the the $i-th$ market are included during and after the crisis period according to the sign of lagged returns:
   - base period : ($\alpha_{i,i} \rightarrow \alpha^{+}_{i,i}, \alpha^{-}_{i,i}$),
   - crisis period: ($\gamma_{i,i} \rightarrow \gamma^{+}_{i,i}, \gamma^{-}_{i,i}$)

The MEM Extended Specification

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1. lagged daily ranges observed in other markets to link together different markets $hl_{j,t-1},\ j \neq i$;
2. time dummies for turbulence periods. Crisis dummy: DC_t (Jul. 1, 1997- Dec. 31, 1998) Post-crisis dummy PC_t (from Jan. 1, 1999 on);
3. interaction terms between 1. and DC_{t-1} to accommodate the possibility that links change their features during the crisis;
4. own asymmetric effects for the the $i-th$ market are included during and after the crisis period according to the sign of lagged returns:
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The MEM Specification: Synthesis

	Label	
$\mu_{i,t} = \omega_i + \beta_i \mu_{i,t-1} + \alpha_{i,i} hl_{i,t-1} (+\psi_i hl_{i,t-2})$	B	Base Model
$+\sum_{j \neq i} \alpha_{i,j} hl_{j,t-1}$	E	Extended Terms
$+\sum_{i=1}^{n} \gamma_{i,j} hl_{j,t-1} DC_{t-1}$	X	Extra Interactions
$+\delta_i DC_{t-1}$	DC	Dummy during crisis
$+\lambda_i PC_{t-1}$	DP	Dummy post-crisis

possibly with asymmetric effects

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possibly with asymmetric effects

Estimation and Testing

Model parameters are estimated on the whole sample period

Statistical tests are used to characterize spillovers

The general model adopted in this context is Model EXD

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A simpler model can be selected by hypothesis testing where the main focus is the existence of spillovers (significance of other markets as a block in the equation) and the difference in their effects during and after the crisis.

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	HK	IN	KO	MA	PH	SI	TA	TH
Other markets	×	×	×	×	×	×	×	×
Other markets during crisis		×	×				×	
Own asymmetric effects			×				×	
Own asymmetries during crisis	×					×	×	×
Shift during crisis		×	×	×	×			
Shift after crisis		×	×					
Lag 2				×		×		×

Markets	HK – MEM(1,1)		IN – MEM(1,1)		KO – MEM(1,1)		MA – MEM(2,1)	
Models	Base	Selected	Base	Selected	Base	Selected	Base	Selected
Loglik	-3267.975	-3265.314	-3447.357	-3434.800	-3696.633	-3694.599	-3032.638	-3029.500
LB(12)	20.920	13.805	51.230	20.545	23.850	13.335	21.729	15.733
	0.052	0.313	0.000	0.057	0.021	0.345	0.041	0.204
LBSQ(12)	20.212	13.087	18.497	12.647	15.899	10.677	14.488	10.958
	0.063	0.363	0.101	0.395	0.196	0.557	0.271	0.533
$\hat{\phi}$		5.61		3.71		6.51		4.41
No spill		2.326		5.978		2.372		3.785
p-value		(0.023)		(0.000)		(0.002)		(0.000)

Markets	PH – MEM(1,1)		SI – MEM(2,1)		TA – MEM(1,1)		TH – MEM(2,1)	
Models	Base	Selected	Base	Selected	Base	Selected	Base	Selected
LogLik	-3155.904	-3149.895	-3036.293	-3032.768	-3446.361	-3444.106	-3549.886	-3546.642
LB(12)	22.307	9.560	11.729	8.651	23.660	16.117	20.586	12.467
	0.034	0.655	0.468	0.732	0.023	0.186	0.057	0.409
LBSQ(12)	2.774	2.215	12.950	7.783	23.288	15.558	15.736	13.496
	0.997	0.999	0.373	0.802	0.025	0.212	0.204	0.334
$\hat{\phi}$		3.57		5.08		4.69		4.68
No spill		5.024		4.053		2.249		4.327
p-value		(0.000)		(0.000)		(0.005)		(0.000)

System Dynamics

The MEM estimated equation by equation should be seen as a system of n equations:

$$\mathbf{hl_t} = \boldsymbol{\mu}_\mathbf{t} \odot \boldsymbol{\epsilon}_\mathbf{t}$$

As per the conditional expectation, allowing for the possibility of a second (own) lag in the estimated MEM, we have

$$\boldsymbol{\mu}_{t+1} = (\boldsymbol{\omega}^* + \boldsymbol{\delta} DC_t + \boldsymbol{\lambda} PC_t) + \mathbf{B}\boldsymbol{\mu}_t + (\mathbf{A}^* + \boldsymbol{\Gamma} DC_t)\,\mathbf{hl}_t + \boldsymbol{A}_2\mathbf{hl}_{t-1}$$

Moving further steps ahead,

$$\begin{aligned}
\boldsymbol{\mu}_{t+2} &= \boldsymbol{\omega} + \mathbf{B}\boldsymbol{\mu}_{t+1} + (\mathbf{A}^* + \boldsymbol{\Gamma} DC_t)\,\boldsymbol{\mu}_{t+1} + \boldsymbol{A}_2\mathbf{hl}_t \\
&= \boldsymbol{\omega} + (\mathbf{B} + \mathbf{A}^* + \boldsymbol{\Gamma} DC_t)\,\boldsymbol{\mu}_{t+1} + \boldsymbol{A}_2\mathbf{hl}_t \\
\boldsymbol{\mu}_{t+\tau} &= \boldsymbol{\omega} + (\mathbf{B} + \mathbf{A}^* + \boldsymbol{\Gamma} DC_t)\,\boldsymbol{\mu}_{t+\tau-1} + \boldsymbol{A}_2\boldsymbol{\mu}_{t+\tau-2}, \\
&= \boldsymbol{\omega} + \mathbf{A}_1\boldsymbol{\mu}_{t+\tau-1} + \mathbf{A}_2\boldsymbol{\mu}_{t+\tau-2}, \text{for } \tau > 2
\end{aligned}$$

which can be solved recursively for any horizon τ.

Impulse Response Functions

Adapting Engle, Ito and Lin we can analyze the dynamic properties of the model by deriving the impulse response functions through the recursive relationship (contemporaneous correlation not considered)

$$\frac{\partial \boldsymbol{\mu}_{t+\tau}}{\boldsymbol{\epsilon}'_t} = \mathbf{A}'_1 \frac{\partial \boldsymbol{\mu}_{t+\tau-1}}{\boldsymbol{\epsilon}'_t} + \mathbf{A}'_2 \frac{\partial \boldsymbol{\mu}_{t+\tau-2}}{\boldsymbol{\epsilon}'_t}$$

initialized by

$$\begin{aligned}
\frac{\partial \boldsymbol{\mu}_{t+1}}{\partial \boldsymbol{\epsilon}'_t} &= \frac{\partial \boldsymbol{\mu}_{t+1}}{\partial \mathbf{hl}'_t} \frac{\partial \mathbf{hl}_t}{\partial \boldsymbol{\epsilon}'_t} = (\mathbf{A}^* + \boldsymbol{\Gamma} DC_t)' \operatorname{diag}(\boldsymbol{\mu}_t) \\
\frac{\partial \boldsymbol{\mu}_{t+2}}{\partial \boldsymbol{\epsilon}'_t} &= (\mathbf{B} + \mathbf{A}^* + \boldsymbol{\Gamma} DC_t) \frac{\partial \boldsymbol{\mu}_{t+1}}{\partial \boldsymbol{\epsilon}'_t} + \mathbf{A}'_2 \frac{\partial \mathbf{hl}_t}{\partial \boldsymbol{\epsilon}'_t} \\
&= \left[(\mathbf{B} + \mathbf{A}^* + \boldsymbol{\Gamma} DC_t) (\mathbf{A}^* + \boldsymbol{\Gamma} DC_t)' + \mathbf{A}'_2 \right] \operatorname{diag}(\boldsymbol{\mu}_t)
\end{aligned}$$

which highlights the peculiarity of the MEM in that the dynamic evolution has an intrinsic dependence on the initial conditions $\boldsymbol{\mu}_t$ and on the extra spillovers estimated in $\boldsymbol{\Gamma}$.

Predictors

The system can be written as the equivalent of a VAR(1)

$$\begin{pmatrix} \mu_{t+\tau} \\ \mu_{t+\tau-1} \end{pmatrix} = \begin{pmatrix} \omega \\ \mathbf{0} \end{pmatrix} + \begin{pmatrix} \mathbf{A}_1 & \mathbf{A}_2 \\ \mathbf{I} & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mu_{t+\tau-1} \\ \mu_{t+\tau-2} \end{pmatrix}$$

$$\tilde{\mu}_{t+\tau} = \omega + \mathbf{A}\tilde{\mu}_{t+\tau-1}$$

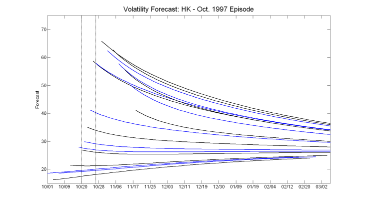
which is useful to derive the long run forecasts

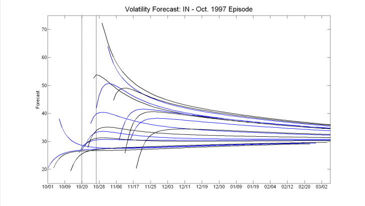
$$\begin{aligned} \tilde{\mu}_{t+\tau} &= \omega + \mathbf{A}\tilde{\mu}_{t+\tau-1} = \omega + \mathbf{A}\left(\omega + \mathbf{A}\tilde{\mu}_{t+\tau-2}\right) \\ &= \left(\boldsymbol{I} + \mathbf{A}\right)\omega + \mathbf{A}^2\tilde{\mu}_{t+\tau-2} \\ &= \left(\boldsymbol{I} + \mathbf{A} + \ldots + \mathbf{A}^{\tau-3}\right)\omega + \mathbf{A}^{\tau-2}\tilde{\mu}_{t+2}, \ \forall\tau > 2 \\ \lim_{\tau\to\infty} \tilde{\mu}_{t+\tau} &= \left(\mathbf{I} - \mathbf{A}\right)^{-1}\omega \end{aligned}$$

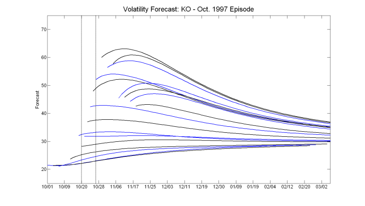
which in our case will differ according to whether t is in one of three subperiods considered.

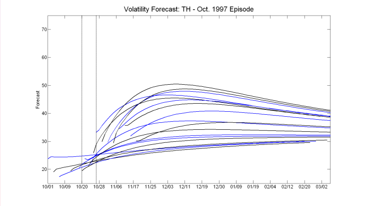
Forecasts: Oct. 1997

Start at a certain date and progress ahead to stress the importance of initial conditions on subsequent forecasts.

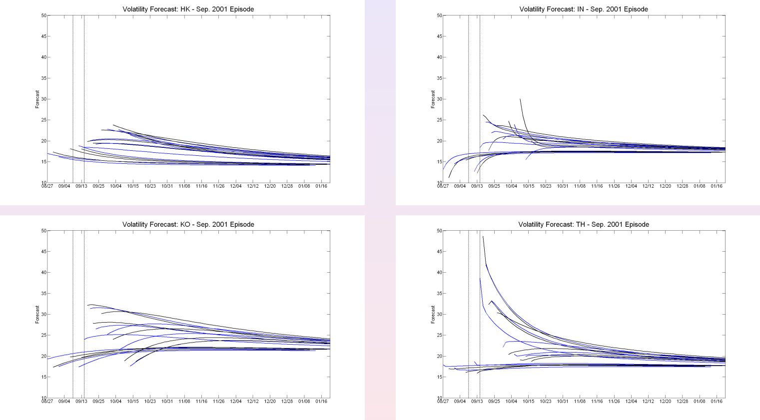








Forecasts: Sep. 2001



Scenario Analysis

$$\begin{pmatrix} hl_{1,t} \\ \vdots \\ hl_{n,t} \end{pmatrix} = \begin{pmatrix} \mu_{1,t} \\ \vdots \\ \mu_{n,t} \end{pmatrix} \odot \begin{pmatrix} \epsilon_{1,t} \\ \vdots \\ \epsilon_{n,t} \end{pmatrix}; \qquad \mathbf{hl_t} = \boldsymbol{\mu}_\mathbf{t} \odot \boldsymbol{\epsilon}_\mathbf{t},$$

We can interpret

$$\boldsymbol{\mu}_t = E\left(\mathbf{hl_t} | \boldsymbol{\epsilon}_\mathbf{t} = \mathbf{1}\right).$$

which can be seen as a baseline solution. Scenario forecast:

$$\boldsymbol{\mu}_t^{(i)} = E\left(\mathbf{hl_t} | \boldsymbol{\epsilon}_\mathbf{t} = \mathbf{1} + \mathbf{s}\right),$$

where $\boldsymbol{\epsilon}_t$ is set at a value bigger than the unit vector.For the i-th market take $s_i = \sigma_i$, the unconditional standard deviation of the distribution of ϵ_{it}. Use contemporaneous covariation within $\boldsymbol{\epsilon}_t$ and choose the other terms $s_j,\ j \neq i$ according to $E\left(\epsilon_{j,t} | \epsilon_{i,t} = 1 + \sigma_i\right) = 1 + \frac{\sigma_{i,j}}{\sigma_i^2}\sigma_i = 1 + \frac{\sigma_{i,j}}{\sigma_i}$.

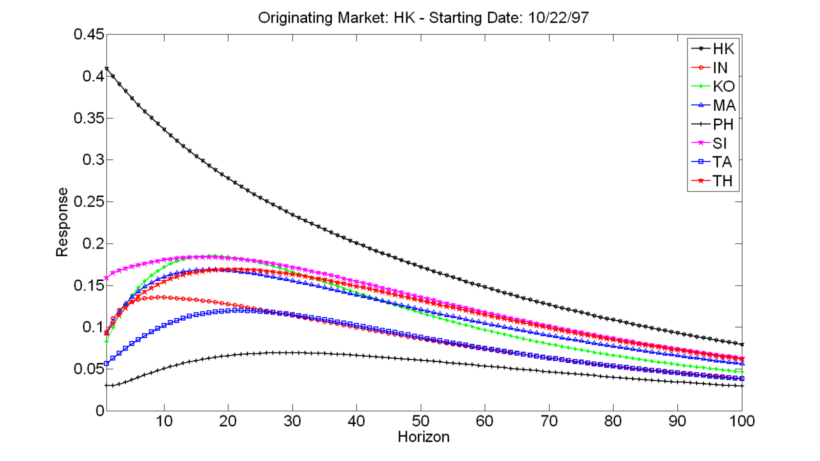
Impulse Response to a Market

Let us define

$$\rho_{t,\tau}^{(i)} = (\boldsymbol{\mu}_{t+\tau}^{(i)} \oslash \boldsymbol{\mu}_{t+\tau}) - \mathbf{1} \quad \tau = 1, \ldots, K$$

as the relative change in the forecast profile started at time t for horizon τ brought about by a one standard deviation shock in the i-th market.

Shock propagation from Hong Kong (Oct., 22, 1997)



Synthesis of Responses

Consider the cumulated responses (area under a curve) from *i* for market *j*

$$\phi_t^{j,i} = \sum_{\tau=1}^{K} \rho_{t,\tau}^{j,i}$$

		From							
		HK	IN	KO	MA	PH	SI	TA	TH
	HK	14.35	0.40	2.33	2.63	0.48	2.27	0.91	2.42
	IN	4.37	1.11	2.01	2.09	0.48	1.78	0.57	1.55
	KO	6.79	0.26	7.18	2.10	0.22	2.07	1.43	1.56
T	MA	10.63	0.27	1.99	9.27	0.69	1.54	0.66	2.60
o	PH	2.87	0.24	0.12	1.87	1.94	1.73	0.86	1.40
	SI	7.84	0.54	2.53	2.41	0.69	6.26	2.39	1.82
	TA	6.47	0.21	2.12	1.13	0.11	1.59	8.78	0.01
	TH	7.07	0.13	2.30	3.01	0.72	1.96	-0.16	6.54

Volatility Spillover Balance

We can build a synthetic measure for a market as the ratio of the average response *from* to the average response *to*

$$\zeta_i = \frac{\sum_{j \neq i} \sum_{t=1}^{T} \phi_t^{j,i}}{\sum_{j \neq i} \sum_{t=1}^{T} \phi_t^{i,j}}$$

	HK	IN	KO	MA	PH	SI	TA	TH
Volatility Spillover Balance	2.39	0.16	0.95	0.88	0.43	0.77	0.74	0.82

Conclusions

- MEMs allow us to model volatility directly (no resort to logs, no multivariate GARCH)
- Dynamic interdependence of volatilities across markets is relevant
- Parameter stability around a crisis
- Momentum effect in forecasting
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