Volume and Volatility in Dual Markets: Lessons from Chinese ADR

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Research Context: Volume volatility nexus

- H-shares and ADRs are identical securities traded in home (SEHK) and host (NYSE) exchanges
- Volatility indicates securities/market performance
- Volatility estimation through lagged and implied volatility measures fail to accurately forecast volatility (Canina and Figlewski RFS); spillovers across countries and securities are time variant and inconsistent
- Volume moves prices (Kyle 1984, Easley and O'Hara 1987); Trading preferences of heterogeneous investors (He and Wang 1995, Harris and Raviv 1993) lead to volume volatility correlation

Research Question

- Do volume and volatility move together OR one leads to the other for Chinese H-shares and their corresponding ADRs?
- In notation,
  - $V(t)$ = volume
  - $h(t)$ = volatility
  - $V(t) = \rho h(t)$ » Correlation test
  - $V(t) \rightarrow h(t)$ » One way causality
  - $h\ (t) \rightarrow V(t)$ » Reverse one way causality
  - $h\ (t) \leftrightarrow V(t)$ » Two way causality

Research Question (contd.)

- Do expected and unexpected volumes contribute to price discovery through volatilities of each H-share and its corresponding ADR? In notation,
  - ADR: h(t) = h(.....EV(t), UV(t))
  - H-share: h(t) = h(.....EV(t), UV(t))
- Do expected and unexpected volumes further contribute to price discovery through the covariance function? In notation,
  - Cov (ADR-r(t), H-share-r(t)) = Cov (.....EV(t), UV(t))

Motivation-
Empirical tests and results

- Volume volatility relations are tested mostly with respect to market or country portfolios; Results are tested against the predictions of MDH or SIAH. The applicability of MDH and SIAH to individual securities is questionable
- Empirical evidence limited and mixed for volume volatility at individual securities level (Harris 1987, Jones et al. 1994, Darrat et al. 2003, Deuskar 2009)

Motivation- Econometrics

- Volatility is unobservable; hence researchers estimate volatility using a model, most commonly GARCH
  - Very powerful ex-post fit but poor forecast
  - Many variations to improve forecast
  - Including 'out of model' parameters improve model performance- volume is a natural candidate
  - Multivariate extensions are promising but computationally challenging (Engle 2004)
    - Return and volatility transmission/spillover studies
    - Different forms of non-stationarity among multiple time series is a BIG problem

Empirical testing:Road map

- Define and estimate volume and volatility. Note volume is observable, volatility needs to be estimated
- Choose an appropriate model for volatility (Criteria?)
- Check stationarity conditions for volume and volatility
- Consider an appropriate model to separate between expected and unexpected volume
- Test the relation between
  - volatility and volume
  - Volatility and expected/unexpected volume

Sample

- 14 Chinese H-shares traded in SEHK and corresponding ADRs traded at NYSE
- Period: From initial registration to Oct 2010
- Descriptive statistics
- Table 1
  - Means and variances are not different; most differences are in higher moments
  - Minimum value (left tail) heavier for H-shares
  - Nos. of observations and hence time duration do not seem to affect standard error

Volume trend stationary?

- Table 2
  - ADF test indicate no unit root and KPSS tests indicate trend stationary. Caveat: fractional integration.
  - Include linear and non-linear (square) trends; residuals must be stationary.
  - Trend equation : $Vol_t = \alpha + \beta t + \chi t^2 + \varepsilon_t$

Volatility GARCH Effect?

- Table 3
  - Auto correlated residuals 3/14; auto correlated squared residuals 14/14
- Table 4
  - TARCH: $\sigma_t^2 = \alpha + \psi\, \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2\, d_{t-1} + \lambda \sigma_{t-1}^2$
  - TARCH model fit for all 14 pairs of ADRs and H-shares
  - Asymmetry denoting bad and good news significant for 8/14 H-shares and 9/14 ADRs
  - Volatility persistence decays slowly (≈0.9) over time

Volatility model with volume

- Table 4
  - TARCH model fit with volume
  - Model: $\sigma_t^2 = \alpha + \psi\ \varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2\ d_{t-1} + \lambda\sigma_{t-1}^2 + \kappa V_{t-1}$
  - Volume is significant for 9/14 ADRs and 5/14
  - Volatility persistence parameter unchanged – confirms Girard and Biswas (2007)

Volatility model with volume

- Table 5
  - One way Granger causality Wald test
  - Model:

$$\sigma_t^2 = \alpha_1 + \sum_{k=1}^{p} \beta_k \sigma_{t-k}^2 + \sum_{k=1}^{q} \theta_k V_{t-k} + \varepsilon_{1t}$$

$$V_t = \alpha_2 + \sum_{k=1}^{m} \delta_k \sigma_{t-k}^2 + \sum_{k=1}^{n} \phi_k V_{t-k} + \varepsilon_{2t}$$

    - Volume to volatility 14/14
    - Volatility to volume 10/14 ADRs 4/14 H-shares

Bivariate GARCH Model

$$\varepsilon_t \mid \Omega_{t-1} = \begin{bmatrix} \varepsilon_{n,t} \\ \varepsilon_{h,t} \end{bmatrix} \sim N(0, H_t)$$

$$H_{n,t} = M_{11} + A_{11}\varepsilon^2_{n,t-1} + B_{11}H_{n,t-1} + C_{11}EV_{n,t-1} + D_{11}UV_{n,t-1} + e_{n,t} \ldots\ldots(9)$$

$$H_{h,t} = M_{22} + A_{22}\varepsilon^2_{h,t-1} + B_{22}H_{h,t-1} + C_{22}EV_{h,t-1} + D_{22}UV_{h,t-1} + e_{h,t} \ldots..(10)$$

$$H_{hn,t} = M_{12} + A_{12}\varepsilon_{n,t-1}\varepsilon_{h,t-1} + B_{12}H_{hn,t-1} + C_{12}EV_{n,t-1}EV_{h,t-1} + D_{12}UV_{n,t-1}UV_{h,t-1} + e_{hn,t} ..(11)$$

ARMA (1,1) with seasonality

$$V_t = \alpha + \sum_{i=1}^{p} \beta_i V_{t-i} + \sum_{j=1}^{q} \delta_j \varepsilon_{t-j} + \eta_k dum_k + \varepsilon_t$$

Bivariate GARCH with/out volume

	A(1,1)	A(1,2)	A(2,2)	B(1,1)	B(1,2)	B(2,2)
No volume	14/14- (+)	14/14 (+)	14/14 (+)	14/14 (+)	14/14 (+)	14/14 (+)
With E(V) and U(V)	14/14 (+)	14/14 (+)	14/14 (+)	14/14 (+)	14/14 (+)	14/14 (+)
	C(1,1)	C(1,2)	C(2,2)	D(1,1)	D(1,2)	D(2,2)
With E(V) and U(V)	12/14 (+)	10/14 8 + / 2 -	7/14 6 + / 1 -	8/14 (+)	14/14 (+)	6/14 (+)

Conclusion

- Modeling daily volatility of ADR and corresponding H-shares listed in Hong Kong Stock Exchange (SEHK)
- Empirical evidence finds
  - Volume and conditional volatility estimated from a GARCH model are contemporaneously correlated
  - Mixed evidence for contemporaneous correlation and lead lag relation between detrended volume and conditional volatility
  - Strong support for bivariate GARCH model in which expected and unexpected volume contribute to volatility directly as well as indirectly through the covariance function
- Volume denotes liquidity in volume volatility relation . EV and UV denote inventory and information components respectively