Risk Everywhere:
Modeling and Managing Volatility

Tim Bollerslev, Benjamin Hood, John Huss, Lasse Heje Pedersen

Discussion by: Liuren Wu

April 29th, 2016
Overview

- Examines volatility behaviors of 50 global macro series over 20 years.
  - Tons of high-frequency data, lots of details
  - Choices existing and enhanced specifications
  - Different estimation approaches

- Key strength lies in balance between
  - academic sophistication v. practical robustness
  - empirical examination v. economic common sense

- Findings will likely become benchmarks for future volatility modeling/forecasting efforts.
Commonality of *risk dynamics*

- **Finding:** Same *Risk* dynamics *Everywhere*
  - The *behaviors/dynamics* of all volatility series look similar up to a scale.
  - Pooled estimation generates more stable parameter estimates and better *out-of-sample* forecasting performance.

- Cannot agree more: This is an important practical direction to go, even if *in-sample* likelihood deteriorates somewhat.
  - RiskMetrics does similar things: \( v_t = .97v_{t-1} + .03r_t^2 \).
    - The same persistence parameter (e.g., \( \phi = 0.97 \)) is applied to all financial series.

- Go further: No estimation necessary: Parameters can be set as *controls*.
  - Set smoothing (\( \phi \)) according to target horizon, very much like fixed-window estimates
    - One-month variance: \( \phi = (.5)^{(1/20)} = 0.966 \)
    - One-year variance: \( \phi = (.5)^{(1/251)} = 0.997 \)
Finding: Same *Risk* dynamics *Everywhere*

- The *behaviors/dynamics* of all volatility series look similar up to a scale.
- Pooled estimation generates more stable parameter estimates and better *out-of-sample* forecasting performance.

Cannot agree more: This is an important practical direction to go, even if *in-sample* likelihood deteriorates somewhat.

- RiskMetrics does similar things: $v_t = 0.97v_{t-1} + 0.03r_t^2$. The same persistence parameter (e.g., $\phi = 0.97$) is applied to all financial series.

Go further: No estimation necessary: Parameters can be set as *controls*.

- Set smoothing ($\phi$) according to target horizon, very much like fixed-window estimates
  - One-month variance: $\phi = (0.5)^{1/20} = 0.966$
  - One-year variance: $\phi = (0.5)^{1/251} = 0.997$
Multi-frequency dynamics

\[ RV_{t+h} - RV_t^{LR} = \sum \beta_j \left( RV_t^j - RV_t^{LR} \right) + e, \quad j = Day, Week, Month \]

- A good starting point with the HAR model, which anchors prediction with multiple frequency components (Day, Week, Month...)

- Practical modifications (enhancements):
  - Each forecasting horizon is estimated separately.
  - Remove the mean parameter with a long-run moving average \((RV_t^{LR})\).

**Why are these enhancements?** — They make economic sense.

- Financial fluctuations are combinations of different cycles
  - Long-run debt cycles, with a duration of several decades/a century
  - Moderate-run productivity (business) cycles, once about every 5 years
  - Monetary policy cycles within/along each business cycle
  - Supply-demand shocks, daily news, emotions, ...

- Shorter cycles must fluctuate within the confines of slower (longer) cycles.
Multi-frequency dynamics

\[ RV_{t+h} - RV_t^{LR} = \sum \beta_j \left( RV_t^j - RV_t^{LR} \right) + e, \quad j = \text{Day, Week, Month} \]

- A good starting point with the HAR model, which anchors prediction with *multiple frequency components* (Day, Week, Month...)

- Practical modifications (enhancements):
  - Each forecasting horizon is estimated separately.
  - Remove the mean parameter with a long-run moving average (\( RV_t^{LR} \)).

*Why are these enhancements?* — They make economic sense.

- Financial fluctuations are combinations of different cycles
  - Long-run debt cycles, with a duration of several decades/a century
  - Moderate-run productivity (business) cycles, once about every 5 years
  - Monetary policy cycles within/along each business cycle
  - Supply-demand shocks, daily news, emotions, ...

- Shorter cycles must fluctuate within the confines of slower (longer) cycles.

---

Bollerslev, Hood, Huss, Pedersen (Wu)  
*Same Risk Everywhere*  
April 29th, 2016 4 / 7
A cascade structure for multi-frequency dynamics

*a cascade of infinite dimensions*

\[ d\nu_t^j = \kappa_j (\nu_t^{j+1} - \nu_t^j)dt + \sigma_j dW_t, \quad j = S, H, D, W, M, Q, Y, C \]

super high-frequency pattern

\[ \ldots = \ldots \]

super long/slow cycles

\[ \kappa_j \text{ controls the frequency/duration of the cycle, } 1/\kappa \text{ is in years.} \]

\[ \text{Roughly power law (geometric) scaling across cycles: e.g., } \kappa_j = 2\kappa_{j+1} \]

\[ \text{One can either estimate } \kappa \text{ or just set them as controls:} \]

\[ \ldots 1/252 \text{ (day), } 1/52 \text{ (week), } 1/12 \text{ (month), } 1/4 \text{ (quarter), } 1 \text{ (year),} \]

\[ 10 \text{ (decade), } 100 \text{ (century), } \ldots \]

\[ \text{There is no long-run mean, but just increasingly longer cycles} \]

Calvet, Fisher, Wu — use the cascade structure to model interest rate dynamics and term structure, but it is equally applicable to variance dynamics
Multi-frequency dynamics in practice

\[ d\nu_t^j = \kappa_j (\nu_t^{j+1} - \nu_t^j) dt + \sigma_j dW_t, \quad j = S, H, D, W, M, Q, Y, C \]

- Practical predication is always a local approximation of the cascade, at the locale of your particular interest.

- Separate estimation (and better yet, separate specification) for each horizon makes perfect sense, with each focusing on a different block of the cascade:
  - Minute-by-minute forecast focuses on intraday patterns — \( RV^{LR} = 1\)-month average.
  - Daily variance prediction — \( RV^{LR} = 1\)-year average.
  - Annual variance prediction — \( RV^{LR} = 10\)-year average.

- The modifications are economically sensible enhancements:
  - Separate estimation for different target horizons — Yes, and maybe also use different frequency components.
  - No long-run mean — Use the next, slower cycle as the local “center.”
  - Common risk dynamics — Same target horizon should focus on the same block of the cascade, with \( 1/\kappa = \)horizon.
Go further

- Go beyond common dynamics: *Same risk everywhere*
  Different financial series also show strong co-movements.
  - Cross-sectional averaging of scaled volatility levels, at least within classes, can directly improve out-of-sample forecasts.
    - The most persistent component tends to be the common component.

- Go beyond autoregression: *Conditional variance* for scenario analysis/stress tests — What happens to the portfolio if
  - Fed raises rates
  - Stock market crashes (e.g., down 30% in one day)
  - Market experiences a protracted recession (e.g., down 30% in one year)

Examples:
- Dupire’s local volatility $\sigma(t, S)$
- Carr and Wu (2016): Option Realized Volatility (ORV) — not only time-weighting but also dollar gamma weighting