Discussion of The Dynamics of Expected Returns: Evidence from Multi-Scale Time Series Modeling

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9th ECB Workshop on Forecasting Techniques
Frankfurt, June 3-4, 2016

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- Bayesian estimation is done by a MCMC algorithm. A simulation study shows that the method works pretty well.

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- Empirical exercise shows that the new model outperforms other benchmarks with increasing horizon (both point and density forecasts)
- Also the optimal allocation in a portfolio-decision problem changes if information from both scales is taken into account.

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- ★ Normality is assumed for both processes x and z. Good for deriving conditional distributions. What is the impact of this assumption? Moreover, how can we justify this?
- ★ Both processes have also constant variances σ_x^2 and σ_z^2. Is this realistic?

Comments: Persistence, ϕ_x and ARMA models

- The paper shows interesting figures to highlight persistence of the new framework for $\phi_x = \phi_z = 0.9$ (Figure 2). The empirical exercise implies that in particular the setting of $\sigma_x^2/\sigma_z^2 = 3$ is interesting. Moreover $\hat{\phi}_x = 0.67$.

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- ★ In addition to this, all Figures are all based on basic AR(1) dynamics. How do things change if we come up with for example an ARMA(2,1) model?
- ★ Moreover: In the simulation setting, Figure 5 (panel B) shows results on estimating back the ACF of the extracted expected returns. The posterior mean is on average 0.10 lower than the theoretical ACF for the multi-scale process for almost all lags.
  All in all, how *sensitive* is this??

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- ★ What about possible structural breaks in both series through time? (since the sample runs from 1952 - 2013).
- ★ There is a huge literature on combining forecasts for real returns, due to unstable relationships. Does it play a role here?

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- Optimal allocation differs: what about the ex-post utility?? Do we gain by incorporating scale-specific information?
- Does the allocation differs over time? (crisis periods etc.)