Discussion of: Barigozzi-Lippi-Luciani - Dynamic Factor Models, Cointegration, and Error Correction Mechanisms

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4. Some suggestions for the application
5. Few minor points, to be discussed separately with the authors

Proposed Model

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4. $\underset{n\times 1}{\xi_t}$: observable idiosyncratic shocks, allowed to be I(0) or I(1), possibly autocorrelated, possibly cross correlated

Model developement 1

- Interpretation of the factors: the structural shocks v_{1t} and v_{2t} are interpreted thrugh SVAR-like restrictions, while the factors F_t are not. It would be interesting to interpret them, since the observed variables are affected by structural shocks through the factors. An interpretation of the factors would also allow for an interpretation of the cointegration vectors β, which might therefore be (over)-identified via suitable restrictions, gaining efficiency and insight

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    3. $H_{0C}(i,j) : \lambda_{ij} = 0$ (meaning: the *i*-th variable is not affected by the *j*-th factor)

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- Measuring the relative relevance of ξ_{it} and $F_{1t}, \cdots, F_{rt}$ (or possibly $v_{11t}, \cdots, v_{1dt}, v_{21t}, \cdots, v_{2(q-d)t}$) in determining the dynamics of x_{it} (something like FEVD): I believe that a major difficulty comes from the fact that the ξ's are allowed to be I(0) or I(1), autocorrelated or not, cross correlated or not.

Application

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- Are $\hat{r}$ and $\hat{q}$ in the benchmark model in differences based on a statistical analysis or they are fixed at 7 and 3?
- Two different/alternative identification schemes are used (sign restrictions to identify the monetary shock, BQ long-run restrictions for the technology shock): it would be preferable to merge the two schemes by first separating the technology shock a la BQ, and then identify the 2 transitory shocks via sign-restrictions.