Comments on "Short-term GDP forecasting with a mixed frequency factor model with stochastic volatility"

P. Poncela

June, 2012

Outline of the talk

- Review

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- Model

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- Data

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- Alternative

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- Conclusions

Review

- Model:

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  - Mixed frequency (monthly and quarterly) dynamic factor model

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  - Stochastic volatility in both the common factor + the idiosyncratic components.

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- Point + density forecasts
- Emphasis: intervals

Model

Measurement equation for $\mathbf{y}_t$

$$\underset{N\times 1}{\mathbf{y}_t} = \underset{N\times 1}{\mathbf{P}} \; \underset{1\times 1}{f_t} + \underset{N\times 1}{\mathbf{u}_t},$$

Common factor and specific components equation

$$\begin{aligned}
\Phi_f(L) f_t &= v_t e^{\lambda_{f,t}}/2, \\
\Phi_q(L) u_{q,t} &= \epsilon_{q,t}\sigma_q e^{\lambda_{q,t}}/2, \\
\Phi_{mj}(L) u_{m,j,t} &= \epsilon_{mj,t}\sigma_{mj} v_t e^{\lambda_{mj,t}}/2
\end{aligned}$$

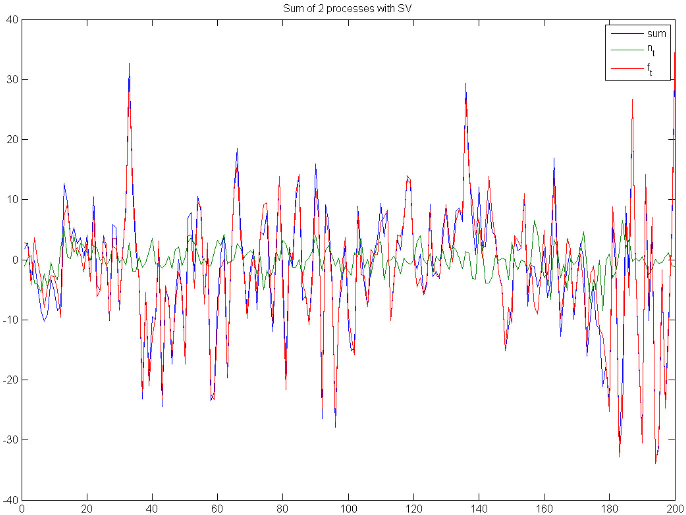
Volatilitities

$$\lambda_{i,t} = \lambda_{i,t-1} + \theta_{i,t}\sigma_{\lambda,i}$$

Model

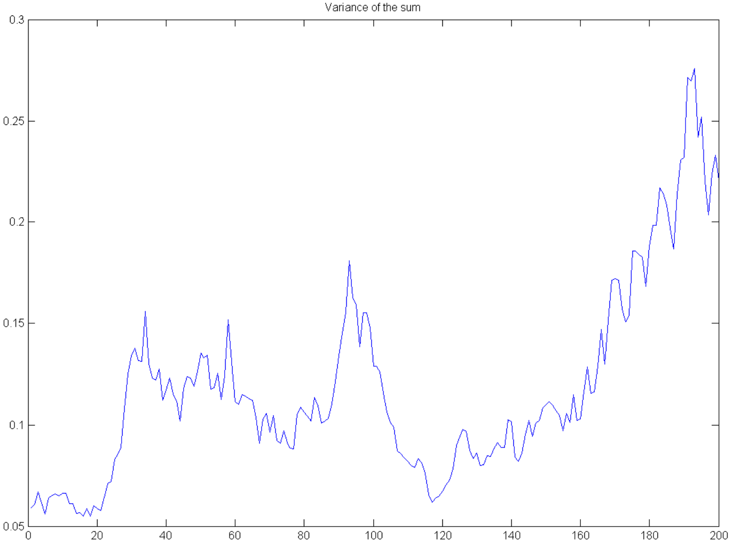
- If I sum 2 processes with SV...
- Why SV in both components?
- How does identification work?
- The proposed model tries to capture changing variance...of what type?

Data



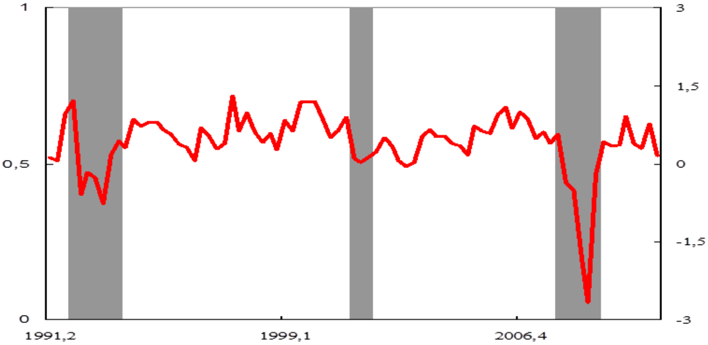
Sum of 2 processes with SV
sum
n_t
f_t
40
30
20
10
0
-10
-20
-30
-40
0
20
40
60
80
100
120
140
160
180
200

Data


Variance of the sum
0.3
0.25
0.2
0.15
0.1
0.05
0
20
40
60
80
100
120
140
160
180
200

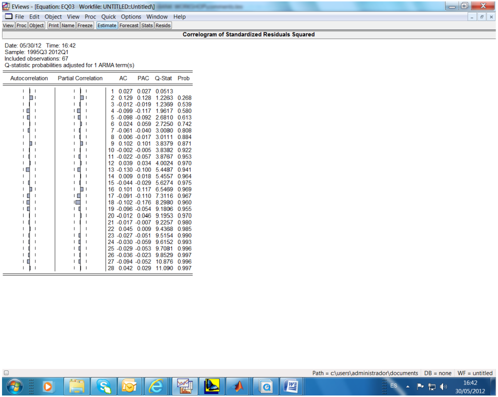
Data

- **Growth rates GDP Euro Area: 1991.1 2011.2 recession periods**



Data

After fitting an AR(1)-ARCH(2), the squared residuals seem OK

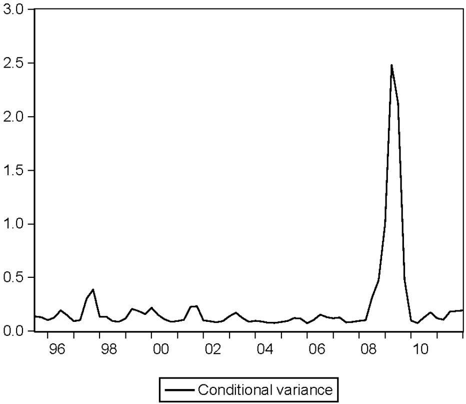


Correlogram of Standardized Residuals Squared

Date: 05/30/12 Time: 16:42
Sample: 1995Q3 2012Q1
Included observations: 67
Q-statistic probabilities adjusted for 1 ARMA term(s)

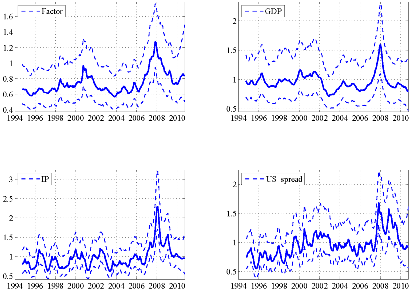
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.027	0.027	0.0513	
		2	0.129	0.128	1.2263	0.268
		3	-0.012	-0.019	1.2369	0.539
		4	-0.099	-0.117	1.9617	0.580
		5	-0.098	-0.092	2.6810	0.613
		6	0.024	0.059	2.7250	0.742
		7	-0.061	-0.040	3.0080	0.808
		8	0.006	-0.017	3.0111	0.884
		9	0.102	0.101	3.8379	0.871
		10	-0.002	-0.005	3.8382	0.922
		11	-0.022	-0.057	3.8767	0.953
		12	0.039	0.034	4.0024	0.970
		13	-0.130	-0.100	5.4487	0.941
		14	0.009	0.018	5.4557	0.964
		15	-0.044	-0.029	5.6274	0.975
		16	0.101	0.117	6.5469	0.969
		17	-0.091	-0.110	7.3116	0.967
		18	-0.102	-0.176	8.2980	0.960
		19	-0.096	-0.054	9.1806	0.955
		20	-0.012	0.046	9.1953	0.970
		21	-0.017	-0.007	9.2257	0.980
		22	0.045	0.009	9.4368	0.985
		23	-0.027	-0.051	9.5154	0.990
		24	-0.030	-0.059	9.6152	0.993
		25	-0.029	-0.053	9.7081	0.996
		26	-0.036	-0.023	9.8529	0.997
		27	-0.094	-0.052	10.876	0.996
		28	0.042	0.029	11.090	0.997

Data



Model + data: SV in common and idiosyncratic components

Figure 2: Stochastic volatility for the common factor and for selected variables



Model + data: SV in common and idiosyncratic components

"To see whether the model picks up any significant time variation in the variances of the common and idiosyncratic errors we plot the posterior median of selected members of Q_t together with their 68% confidence bands (Figure 2)."

- Do we need SV both in the common factor and idiosyncratic component?

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- Do we need SV both in the common factor and idiosyncratic component?
- Can we make the common stochastic volatility more common?

Extracting nonlinear signals in multivariate setups

Figure 3: RMSE at different releases

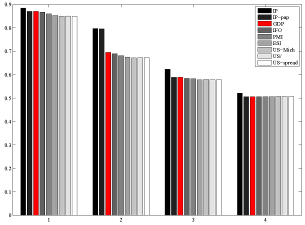
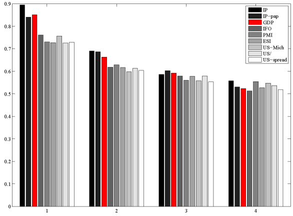


Figure 4: Forecast dispersion at different releases



Extracting nonlinear signals in multivariate setups

Measurement equation for $\mathbf{y}_t$

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Common factor and specific components equation

$$\begin{aligned} f_t &= \mu_{s_t} + a_t \\ \Phi_q(L)u_{q,t} &= \epsilon_{q,t}\sigma_{q,s_t} \\ \Phi_{mj}(L)u_{m,j,t} &= \epsilon_{mj,t}\sigma_{mj,s_t} \end{aligned}$$

Transition probabilities

$$p(s_t = j | s_{t-1} = i, s_{t-2} = h, ..., I_{t-1}) = p(s_t = j | s_{t-1} = i) = p_{ij}$$

- $\mathbf{u}_t$ is $(0, \mathbf{\Sigma}_u)$. In classical factor analysis, $\mathbf{\Sigma}_u$ is diagonal.

Extracting nonlinear signals in multivariate setups

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- I_t is the information set up to period t.

Alternative: Literature review

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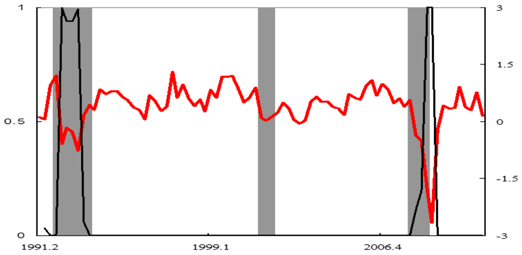
- Chauvet and Hamilton (2006), Hamilton (2011)
- Camacho, Perez-Quiros and Poncela (2012) with mixing frequencies and ragged ends

Alternative

- Growth rates GDP Euro Area: 1991.1 20011.2 recession periods and probability of recession



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Extracting nonlinear signals in multivariate setups

Let $I_t^* = \left\{ (f_{\tau|\tau}^*)_{\tau=1}^{\tau=t} \right\}$,

$$prob(s_t = j | I_t^*) = \frac{f(f_{t|t}^* | s_t = j, I_{t-1}^*) prob(s_t = j | I_{t-1}^*)}{f(f_{t|t}^* | I_{t-1}^*)}$$

- What about the news content of the observations? The filtered linear common factor is a weighted average of all observations (present and past)

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Misspecified common factor estimator

$$f_{t|t}^* = \sum_{\tau=1}^{t} \mathbf{w}_{t,\tau} \mathbf{y}_\tau$$

Extracting nonlinear signals in multivariate setups

- How observations are weighted?

$$\mathbf{w}_{t,t} = \frac{1}{c_t}\mathbf{P}'\boldsymbol{\Sigma}_u^{-1}$$
$$\mathbf{w}_{t,\tau} = \frac{1}{c_\tau}\frac{1}{V_{\tau|\tau-1}}\phi\mathbf{w}_{t,\tau+1} \text{ for } \tau = t-1, ..., 1$$

where c_t and $V_{t|t-1}$ are $f\left(\mathbf{P}'\boldsymbol{\Sigma}_u^{-1}\mathbf{P}, \phi\right) = f\left(\sum_{i=1}^{N}\frac{\lambda_i^2}{\sigma_i^2}, \phi\right)$.

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  - the signal to noise ratios
- High volatile observations have less weight....

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- For macro applications: do we need SV in both components (common and idiosyncratic)?
- Challenge against models that try to capture the same features