Comment on 'Practical mehods for modelling weak ARMA processes: identification, estimation and specification with a macroeconomic application' by J-M. Dufour and D. Pelletier

Stéphane Gregoir (stephane.gregoir@edhec.edu)

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Motivation

1. VAR vs. VARMA
    - VAR models have numerous drawbacks: not parsimonious, not closed under marginalization, temporal aggregation and subsampling but easy to estimate and use
    - VARMA are more parsimonious, closed under marginalization, temporal aggregation and subsampling, but difficult to identify and estimate
2. a large number of classes of strictly stationary non-linear processes satisfy a VARMA representation in which the innovations are only uncorrelated (and not i.i.d. or satisfying a m.d.s property): VARMA weak representation

The authors focus on a subclass of VARMA processes easier to estimate and use (identification, estimation and specification)

Identification

$\Phi(L)$ and $\Theta(L)$ must be unique for a given $\Phi(L)^{-1}\Theta(L)$, different ways to get an identified representation (left-coprime operators)

- Echelon form : complex parameterization (McMillan Degree + set of Kronecker indices)
- Final AR or MA equation form : may be associated to not parsimonious models
- Diagonal MA equation form : introduction of this new set of models which can be read as a VAR model with individual MA error terms
  - assumption 3.6: when the MA polynomial associated to an error term has no common root with the autoregressive polynomials of the corresponding column, the diagonal MA equation form is an identified model

Question: can we construct descriptive statistics based on (partial) autocovariance fonctions that would point to the diagonal MA equation form as an appropriate model for a set of variables ?... canonical correlations (Tsay and Tiao (1985))

Estimation and specification

Follows Hannan-Kavalieris (1984) and Hannan, Kavalieris and Mackisack (1986) approach: three steps of OLS/GLS and a selection of the polynomial degrees based on information criteria

Three step approach that lead to estimators that have the same asymptotic var-covar matrix as maximum likelihood and non-linear least squares estimators (depending on the properties of the innovation process)

Minor questions:

- The orders in case of diagonal MA equation form are selected equation by equation in the second step: the AR order may be too short and cross-correlations may be neglected ? what is the impact of not using GLS third step ?
- proof of the consistent estimation of the order p and q : the cases $(p \leq p_0,\ q \leq q_0)$ and $(p \geq p_0,\ q \geq q_0)$, but can we get an insight for the cases $(p \leq p_0,\ q \geq q_0)$ and $(p \geq p_0,\ q \leq q_0)$

Convincing results in three simulation exercises

Remarks

1. About the motivation:
   - VARMA models can forecast macroeconomic variables more accurately than VARs (Athanasopoulos and Vahid (2008)), many macroeconomic variables satisfy models with MA component (Chen, Choi and Escanciano(2012)), Dynamics of basic real business cycle models often follow VARMA representation incompatible with VARs (Cooley and Dwyer (1998))
   - interest in forecasts and impulse response functions but direct forecasts outperform iterated forecasts in case of misspecification (Bhansali (2002)) and robust impulse responses can be estimated as the difference between two direct forecasts (Koop, Pesaran and Potter (1996) and Jorda (2005):
     $IR(t, h, \eta) = E(y_{t+h} \mid \epsilon_t = \eta, X_t) - E(y_{t+h} \mid \epsilon_t = 0, X_t))$
2. in case of non-linear strictly stationary process, IR as difference between two direct forecasts vs. IR derived from a VARMA representation