Testing multi-horizon causality and causality measures in VAR models: Two new user-written functions for the Gretl time series menu

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Extended abstract

Granger (1969) introduced the concept of Granger causality (CG), defined in terms of predictability one period ahead (horizon $h = 1$) which is sufficient as a dynamic characterization (predictability) only in bivariate models. For, - dimensionally - larger models, the GC concept is not adequate as causal chains might go undetected, a point made by Lütkepohl (1993), Lütkepohl & Burda (1997) and Lütkepohl (2005, p. 41-51 and 105-108). Under the presence of "auxiliary" variables, non-causality at horizon one $h = 1$, is neither a necessary nor a sufficient condition for a series of interest to be ineffective in predicting another series of interest at longer horizons (forecasting horizons equal or greater than two). Dufour & Renault (1998) generalized the concept of GC and provided the theoretical framework underlying causality at any given horizon $h > 1$.

The statistical procedure, as well as, tests for the corresponding multi-horizon non-causality hypotheses, were developed by Dufour, Pelletier & Renault (2006, DPR) in the context of finite-order vector autoregressive models. Their methodology is based on multiple-horizon vector autoregressions (called *(p,h)-autoregressions*) where the parameters of interest can be

estimated and tested by linear methods. Importantly, while the hypotheses considered are nonlinear functions of a standard VAR(p) model, (*(p,1)-autoregression*), the proposed methods only require linear regression techniques with heteroscedastic autocorrelation consistent (HAC) standard errors and Gaussian asymptotic distributional theory is available. DPR further consider a bootstrap procedure that could alleviate the unreliability of asymptotic approximations for VAR models in small samples. Finally, the DPR method can be readily applied to a nonstationary vector of variables without relying on pre-testing for the presence of cointegration and subsequent reduced rank specifications. The lag augmented VAR in levels approach adopted by Dufour et al. (2006) in their underlying *(p,h)-autoregressions,* can handle nonstationary vectors of variables that admit possibly different integration orders, as long as the maximal integration order among the series can be established.

The DPR statistical procedure allows the distinction of short run (small forecast horizon) and long-run (long forecast horizon) causality, although there is no immediate statistical characterization of those states. Such a distinction can be particularly relevant in view of slowly moving nonstationary macro variables that could predict each other with possibly long lags (delays). Finally, the DPR procedure allows the investigation of causal chains since multiple horizon causality allows one to account for indirect causal links (transmitted through different variables across time) and discuss potential causal neutralization.

Once multi-horizon causality has been established, empirical researchers might want to measure the strength of the dynamic relationships and causal links. Notice that existing causality measures have been defined only for the horizon 1, and they fail to capture indirect causality. Dufour and Taamouti (2010, DT) developed a statistical approach that adequately covers the problem of measuring causality between two vector processes at any given horizon. In effect, the proposed measures generalize (to any horizon $h \geq 1$) the measures introduced by Geweke (1982). Their approach is intuitive and easy to interpret without highly restrictive parametric models as they propose a simple simulation-based method to evaluate the measures for any VARMA model. In addition they describe asymptotically valid nonparametric confidence intervals, based on a bootstrap technique.

In this work we build a gretl function package for applying the DPR procedure using the data set considered by DPR, that is the one used by

Bernanke and Mihov (1998) in order to study United States monetary policy. This data set consists of monthly observations on nonborrowed reserves (NBR), the federal funds rate (R), the gross domestic product deflator (P), and real gross domestic product (GDP). The monthly data on GDP and GDP deflator were constructed using state space methods from quarterly observations (Bernanke and Mihov, 1998). The sample runs from January 1965 to December 1996 for a total of 384 observations. All variables are in logarithmic form and transformed by taking first differences. Hence, causality relations are interpreted in terms of growth rates.

A help text and a sample script have been built to replicate DPR and to ease applied researchers in their inferences. The package is introduced in the gretl's menu: Model -> Time series -> Multi-horizon causality. It offers a highly flexible GUI to choose amongst a number of different specifications for the *(p,h)-autoregression* accommodating different deterministic trend models and orders of integration. On a successful call, it allows extraction of a large number of elements from the DPR procedure.

In addition, a second gretl package for the DT procedures has been built again using the data by DT to replicate their results and to facilitate applied research. This is the same Bernanke and Mihov (1988) dataset with a stationarity adjustment made to the inflation rate. We also provide a relevant help text and a sample script to facilitate replication. The package can be run through a GUI from the gretl menu: Model -> Time series -> Multi-horizon Causality measures. On a successful call, it allows extraction of a large number of elements from the DT procedure and provides a detailed graph of estimated causality measures and their bootstrap confidence interval across horizons, $h \geq 1$.

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