TAKEHOME FINAL EXAM

(1) The course website has a data file (one text version and one .RData version) that contains quarterly data for the US real inventory-change to real GDP ratio.

(a) Use those data and frequency domain methods to show that this series, which is based on seasonally adjusted data, probably has less power at the seasonal frequencies than the "true" seasonal component of the series. [Note that for economic data plots of logged spectral densities are usually easier to interpret than plots of level spectral densities].

(b) Explain why, if an autoregressive model with long lags is fit to these data, the fitted model is likely to imply unrealistically accurate forecasts.

(c) The following bivariate VAR has been estimated from monthly data (not the data you used above). Show that it implies strong seasonal oscillations in the data.

$$y_t = \begin{bmatrix} 1.3160254 & 0.4160254 \\ 0.4160254 & 1.3160254 \end{bmatrix} y_{t-1} + \begin{bmatrix} -1 & 0 \\ 0 & 0 \end{bmatrix} y_{t-2} + \varepsilon_t$$

(2) A practical problem in constructing forecasting models is that data are often available at mixed time intervals. For example, GDP is available quarterly, while interest rates, CPI, and asset price variables are available at monthly or finer intervals.

(a) Explain in detail how the Kalman filter could be used to estimate a VAR in GDP, CPI, and interest rates using the raw quarterly and monthly data. Your method should *not* involve a preliminary stage of interpolating the GDP data to create an artificial monthly GDP series. Note that GDP conceptually aggregates the flow of production across the whole quarter.

(b) The Kalman filter can also be used, when the data are all at the same time unit, to estimate a VAR with time varying parameters, treating the parameters β_t as the state vector and using $\beta_t = \beta_{t-1} + \varepsilon_t$ as a plant equation. Explain in detail how to set up the Kalman filter to do this.

(c) The Kalman filter can also be used, when the model has constant parameters and the data are all at the same time unit, to handle a data set in which values are missing for some variables and some dates. Explain in detail how to set up the Kalman filter to do this.

(d) Suppose you have a data set that mixes GDP, an interest rate, and CPI (the latter two monthly), that there are some missing observations, and that parameters are time varying. Explain why the Kalman filter cannot be applied directly in this case. Suggest how you could nonetheless proceed, using MCMC methods.

Date: January 15, 2011.

©2011 by Christopher A. Sims. This document is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 3.0 Unported License.

(3) Here's a really old-fashioned "multiplier-accelerator" model:

$$\begin{aligned} Y_t &= C_t + I_t + A + \xi_t \\ C_t &= .7Y_t + .3Y_{t-1} + \nu_t \\ I_t &= .2(Y_t - Y_{t-1}) + .3I_{t-1} + \varepsilon_t \,. \end{aligned}$$

(a) If we treat the shocks ξ_t ("autonomous expenditure"), ν_t and ε_t as mutually independent, i.i.d. mean zero normal random variables, is this model identified at the parameter values shown? Note that the coefficients on C and I in the first equation are not estimated; they are known to be 1. The other right-hand side coefficients are all to be estimated.

(b) Now suppose that someone tries to estimate this model as an SVAR, using for identification only the restrictions the model places on contemporaneous coefficients (i.e. on A_0 in the usual SVAR notation.) Is the model identified using only these restrictions?

(c) Do the shocks in this model span the innovation space? (I.e., is the model "invertible"?)