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A BAYESIAN NOTE ON COMPETING CORRELATION STRUCTURES IN THE DYNAMIC LINEAR REGRESSION MODEL

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A BAYESIAN NOTE ON COMPETING CORRELATION STRUCTURES IN THE DYNAMIC LINEAR REGRESSION MODEL

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A Bayesian posterior odds approach is used to distinguish between different error correlation structures in dynamic linear regression models. We extend the usual framework to general elliptical error distributions and any number of lagged dependent variables and contending correlation hypotheses. In contrast to classical tests, posterior analysis is not fundamentally affected by the dynamic structure of the model, and is very easily performed in a reference prior case. Recent classical results are provided with a Bayesian interpretation, and a small empirical example illustrates the approach.

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1. Introduction

In a recent article, Inder (1990) proposed a test for autocorrelated errors in the linear regression model with one lagged dependent variable among the regressors, thus generalizing King (1985) to dynamic regression models. Although Inder's extension seems somewhat **ad hoc**, he reports evidence from simulation experiments that favours his test over the widely used h and t tests from Durbin (1970) as well as the Durbin-Watson test.

In this paper we consider a Bayesian posterior odds approach to the question addressed in Durbin (1970) and Inder (1990). In fact, we develop our results within a much more general framework, where we compare m dynamic models (each with q lagged dependent variables) that differ only in their covariance structure. In addition, we allow for general elliptical distributions of the error vector. We show that Bayesian posterior analysis is not fundamentally affected by the dynamic character of the model, and posterior odds are obtained in the same fashion as in Chib **et al**. (1990), who treat the static case. Indeed, posterior results are based on the likelihood function, the functional form of which is not changed by introducing dynamics. Within a Bayesian framework, the latter will only complicate prediction [see Chow (1973)].

Section 2 describes the Bayesian model, giving rise to the posterior analysis under a reference prior in Section 3. In Section 4 we compare our method with Inder's (1990) in the special case considered by him. An application to Durbin and Watson's (1951) consumption of spirits data in Section 5 illustrates our approach. The final section contains some concluding remarks.

2. The Bayesian Model

We consider m dynamic linear regression models (i = 1,...,m)

$$M_i : y = Y_{-1}\alpha + X\beta + \varepsilon \tag{1}$$

where Y_{-1} is an $n \times q$ matrix containing lagged values of the n dimensional vector y as well as the necessary initial values y_0, and X groups k other weakly exogenous variables. The error vector ε is assumed to have an n-variate elliptical distribution with location vector 0 and dispersion matrix $\sigma^2 V_i$, with σ^2 a common scale factor, and $V_i = V_i(\eta_i)$ a model specific PDS matrix function of the ℓ_i dimensional η_i. The m models thus only differ in the structure of V_i.

For notational convenience, let $Z = (Y_{-1}\ X)$ and $\gamma' = (\alpha'\ \beta')$. As a result of the unitary Jacobian of the transformation from ε to y, the data density corresponding to M_i is:

$$p(y|y_0, X, \gamma, \sigma^2, \eta_i, M_i) = (\sigma^2)^{-\frac{n}{2}}|V_i|^{-\frac{1}{2}}$$

$$g_i[(y - Z\gamma)'\sigma^{-2}V_i^{-1}(y - Z\gamma)]. \tag{2}$$

In (2) the nonnegative function $g_i[.]$ is such that $u^{\frac{n}{2}-1} g_i(u)$ is integrable in $\mathbb{R}_+$, $i = 1,\dots,m$; see Dickey and Chen (1985). This general class covers many specific multivariate densities, like Normal, Student t or Pearson II. Due to the linearity of the transformation from ε to y, the data density still belongs to the elliptical class. Finally, the entire analysis will be conducted conditionally upon y_0. For alternative treatments of initial values see e.g. Zellner (1971).

In order to complete the Bayesian model, we specify a prior density on the parameters of M_i:

$$p(\gamma, \sigma^2, \eta_i) = c_1\sigma^{-2}p(\gamma)p(\eta_i), \tag{3}$$

a product of the usual improper prior on σ^2, a prior on the common coefficients γ, and a **proper** prior on η_i, with $c_1 > 0$.

3. Posterior Analysis

The Jeffreys' type prior on σ^2 can be shown, as in Osiewalski and Steel (1990), to lead to exactly the same joint density of (y, γ, η_i) as under Normality of the disturbances in (1), namely

$$p(y, \gamma, \eta_i | y_0, X, M_i) = c_1 \Gamma(\tfrac{n-k-q}{2}) \, \pi^{-\frac{n-k-q}{2}} p(\gamma) p(\eta_i)$$

$$h_i(\eta_i) f_s^{k+q}(\gamma | n-k-q, \hat{\gamma}_i, \frac{n-k-q}{SSE_i} Z'V_i^{-1}Z), \tag{4}$$

with $$h_i(\eta_i) = |V_i|^{-\frac{1}{2}} |Z'V_i^{-1}Z|^{-\frac{1}{2}} (SSE_i)^{-\frac{n-k-q}{2}}, \tag{5}$$

and the (k+q)-variate Student t density appearing in (4) has n-k-q degrees of freedom, location vector $\hat{\gamma}_i = (Z'V_i^{-1}Z)^{-1}Z'V_i^{-1}y$ and the precision matrix involves $SSE_i = (y - Z\hat{\gamma}_i)'V_i^{-1}(y - Z\hat{\gamma}_i)$; finally, we implicitly assume Z to be of full column rank.

Clearly, γ can be integrated out analytically from (4) if we assume an improper uniform prior in (3)

$$p(\gamma) = c_2. \tag{6}$$

This convenient case will be treated here in some detail, whereas for independent Student t priors on γ the results in Chib et al. (1990) can easily be adapted. Remark that in the context of dynamic models the choice of (6) does not exclude nonstationarity of the process for y. Imposing stationarity requires restricting the parameter space of α, which would add q dimensions to the numerical integration in the sequel. Of course, Inder's (1990) procedure does not impose stationarity either.

Under M_i, the use of (3) and (6) leads to the Student t conditional posterior of γ, given η_i, implicit in (4), and the following marginal posterior of η_i:

$$p(\eta_i | y, y_0, X, M_i) = K_i^{-1} h_i(\eta_i) p(\eta_i), \tag{7}$$

where we assume $K_i = \int h_i(\eta_i)p(\eta_i)d\eta_i$ to be finite, $i = 1,\dots,m$. Evaluating K_i only requires ℓ_i dimensional numerical integration. Assigning prior probability $p(M_i)$ to the i-th model, the posterior probability is now given by

$$p(M_i|y,\ y_0,\ X) = \frac{p(M_i)K_i}{\sum_{j=1}^{m} p(M_j)K_j}, \tag{8}$$

since the (improper) predictive densities are $p(y|y_0,\ X,\ M_j) = cK_j$ with the same constant c for all $j = 1,\dots,m$. The Bayes factor B_{rs} for comparing M_r and M_s is equal to K_r/K_s leading to the posterior odds $[p(M_r)/p(M_s)] \times B_{rs}$. Note that B_{rs} could take any value if we would allow $p(\eta_i)$ in (7) to be improper.

If the loss structure penalizes all incorrect decisions equally heavy, the Bayesian pretest procedure amounts to choosing the model with highest posterior model probability. In order to avoid pretesting, we can use mixtures of data densities, as explained in Chib **et al.** (1990).

4. Comparison with Inder's Test for Autocorrelated Disturbances

In the particular case where $m = 2$, $q = 1$ and the errors either follow a stationary AR(1) process or are uncorrelated, Inder (1990) proposes a modification of King's (1985) test for AR(1) in the static regression model. He suggests replacing the dynamic coefficient α by its OLS estimate obtained from (1), say

$$a = (y_{-1}'\ \bar{P}_X\ y_{-1})^{-1}\ y_{-1}'\ \bar{P}_X\ y, \tag{9}$$

where we define

$$\bar{P}_w = I_n - W(W'W)^{-1}W', \tag{10}$$

and Y_{-1} is now a vector denoted by y_{-1}. Inder's test statistic is then given by

$$s(a,\eta_1^*) = \frac{(y-y_{-1}a)'Q'\bar{P}_{QX}Q(y-y_{-1}a)}{(y-y_{-1}a)'\bar{P}_X(y-y_{-1}a)}, \tag{11}$$

where $Q'Q = V_1^{-1}(\eta_1^*)$, and the AR(1) correlation structure is generally given by

$$V_1(\eta_1) = [(1-\eta_1)^2 I_n + \eta_1 A - \eta_1^2 B]^{-1}, \tag{12}$$

with $\eta_1 \in (0,1)$, $B = \mathrm{Diag}(1,0,\ldots,0,1)$, and A is a tridiagonal matrix with 2 on the main diagonal and -1 on the other two diagonals. Contrary to the Bayesian approach in Section 3 where η_1 is integrated out, Inder tests against a specific alternative by choosing a particular value $\eta_1 = \eta_1^*$.
In the static case (q = 0) this fact results in the equivalence of King's (1985) test statistic and the Bayes factor (BF) conditional on $\eta_1 = \eta_1^*$, given by $h_1(\eta_1^*)/h_2$, as explained in Chib **et al.** (1990). However, the extension to dynamic models deprives Inder's test statistic in (11) of the same Bayesian interpretation. In particular, the conditional BF is from (5) with $V_2 = I_n$

$$\frac{h_1(\eta^*{}_1)}{h_2} = \frac{|Q'Q|^{\frac{1}{2}}|Z'Q'QZ|^{-\frac{1}{2}}}{|Z'Z|^{-\frac{1}{2}}} \left[\frac{y'Q'\bar{P}_{QZ}Qy}{y'\bar{P}_Z y}\right]^{-\frac{n-k-1}{2}}, \tag{13}$$

where elements of y now appear through Z as well. The dynamic character of the model thus precludes a direct link with a test statistic of the simple ratio form in (11). In addition, the conditional BF in (13), contrary to (11), uses all regressors in the same fashion, and does not distinguish between lagged y's and other regressors. Indeed, for posterior inference the form of the likelihood suffices, and the sampling properties of the actual data density are entirely irrelevant.

If we condition on α as well, a Bayesian interpretation of (11) can be provided, as the conditional BF given $\alpha = \alpha^*$ and $\eta_1 = \eta_1^*$ takes the form

$$\frac{|Q'Q|^{\frac{1}{2}}|X'Q'QX|^{-\frac{1}{2}}}{|X'X|^{-\frac{1}{2}}} [s(\alpha^*, \eta_1^*)]^{-\frac{n-k}{2}}, \tag{14}$$

where elements of y now only appear through

$$s(\alpha^*,\eta_1^*) = \frac{(y-y_{-1}\alpha^*)'Q'\bar{P}_{QX}Q(y-y_{-1}\alpha^*)}{(y-y_{-1}\alpha^*)'\bar{P}_X(y-y_{-1}\alpha^*)}. \tag{15}$$

In the static case where $\alpha^* = 0$, (15) reduces to Kings (1985) statistic. Inder's (1990) suggestion in (11) for dynamic models amounts to evaluating (15) at the OLS value a for α^*. While a is the posterior mean and mode of α given $V_2 = I_n$ it can clearly be far from the posterior mean and modal values of α under the AR(1) alternative.

From the Bayesian perspective adopted here, we naturally suggest to base model comparison on the unconditional BF B_{12}, which only requires univariate numerical integration, and fully takes the uncertainty concerning both α and η_1 into account. Clearly, this approach can trivially cope with any number of lagged y's (general q)[1)] in the dynamic regression models (1) and is immediately suited to compare more than two alternatives at the same time (general m), leading in a natural fashion to finite mixtures of contending models [see Chib **et al.** (1990)].

5. An Empirical Example

As an illustration of the ideas developed in the paper, we consider the application found in Durbin and Watson (1951). The example deals with the annual consumption of spirits in the United Kingdom from 1870-1938. The explanatory variables are per-capita income and the price of spirits (deflated by a cost-of-living index). The model, which includes a constant, is linear in logs. Although it is possible to deal with many different contending correlation structures, consider the choice between $V_1(\eta_1)$ as given in (12), and $V_2 = I_n$. The prior information is summarized by (3) and (6) with $\eta_1 \sim \text{Uniform}(0,1)$. The posterior results which are provided in Table 1, clearly indicate that the AR(1) process is strongly supported by the data; the BF in favour of V_1 is $9.46 * 10^{13}$.

Since we are proposing the use of unconditional BF's we point out that for this data set the BF in its conditional version, can be dramatically different. For example, if we condition on $\eta_1^* = 0.5$, the prior mean of η_1, the BF is reduced to 348730. Finally, if we evaluate the BF in (14) at $\alpha^* = 0.73$, the OLS value, and let $\eta_1^* = 0.5$, the BF drops to 1468. Although in this case the evidence nonetheless supports the AR(1) process,[2] the enormous difference between the conditional and unconditional BF deserves attention.

Pursuing this example a bit further, we redo the analysis with the variables specified in first differences (denoted by tildes). Differencing seems appropriate for this data because the posterior density of η_1 monotonically increases over (0,1). Again, we compare uncorrelated (M_2) and AR(1) (M_1) error covariance structures. Now using the reference prior with $\eta_1 \sim$ Uniform(-1,1), we find that the BF in favour of the AR(1) process is 0.25. Table 2 presents some results under individual models as well as when the models are mixed with the posterior probabilities.

6. Conclusion

This paper has proposed the use of a posterior odds approach to distinguish between contending correlation structures in dynamic linear regression models. We show that, contrary to classical tests, posterior analysis is not fundamentally affected by the dynamic structure of the model. In addition, the framework provides an effective means of dealing with more than one lagged dependent variable, and more than two contending models, thus relaxing the set-up of Inder (1990). In several cases of interest, the calculations are quite straightforward and may be readily implemented in applied work.

Footnotes

1) Of course, we require Z to remain of full column rank, so that $q < n-k$.
2) Also, Inder's $s(0.73, 0.5) = 0.8429$, which rejects M_2 at 5%.

Table 1. Posterior results for levels models.

		M_1	M_2
$p(M_i)$		0.5	0.5
$p(M_i \mid y, y_0, X)$		1.0000	0.0000
		mean (s.dev.)	mean (s.dev.)
$p(\alpha \mid y, y_0, X, M_i)$		0.07 (0.08)	0.73 (0.07)
$p(\beta \mid y, y_0, X, M_i)$	constant	2.22 (0.54)	1.25 (0.36)
	income	0.66 (0.17)	0.01 (0.07)
	price	-0.90 (0.09)	-0.38 (0.09)
$p(\eta_1 \mid M_1)$		0.50 (0.29)	-
$p(\eta_1 \mid y, y_0, X, M_1)$		0.99 (0.01)	-

Table 2. Posterior results for models in first differences.

		M_1	M_2	mixture M_{12}
$p(M_i)$		0.5	0.5	-
$p(M_i \mid \tilde{y}, \tilde{y}_0, \tilde{X})$		0.20	0.80	-
		mean (s.dev.)	mean (s.dev.)	mean (s.dev.)
$p(\alpha \mid \tilde{y}, \tilde{y}_0, \tilde{X}, M_i)$		0.09 (0.09)	0.06 (0.08)	0.07 (0.08)
$p(\beta \mid \tilde{y}, \tilde{y}_0, \tilde{X}, M_i)$	income	0.69 (0.16)	0.69 (0.16)	0.69 (0.16)
	price	-0.89 (0.09)	-0.89 (0.09)	-0.89 (0.09)
$p(\eta_1 \mid M_1)$		0.00 (0.57)	-	-
$p(\eta_1 \mid \tilde{y}, \tilde{y}_0, \tilde{X}, M_1)$		-0.11 (0.14)	-	-

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