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Editorial

Special Issue on "Estimation, Testing and Forecasting in Econometrics"

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One of us (King) joined Monash University as a young lecturer in econometrics in 1979. At about that time, there was a noticeable leap in the availability of computer power that allowed us to contemplate a likelihood based approach to econometrics. For example, the Faculty of Economics and Politics had taken delivery of its own VAX11/780 mini computer which allowed serious statistical and econometric computations to be made in double precision if required. Econometricians no longer had their CPU time rationed. We finally had the computational power and ability to run maximum likelihood estimation for most models and consequently conduct likelihood ratio (LR) tests or if more convenient, Lagrange multiplier (LM) or Wald tests. Did these advances mean that the theory of econometrics was "sorted"?

It didn't take long for cracks to appear. One testing problem that generated a disproportionately large literature in econometrics is that of testing for first-order autoregressive disturbances in the linear regression model, see King [5] for a survey. Here the LR test was found to be a very poor performer [1]. Unit root testing is another area where the classical tests (LR, LM and Wald) were found to perform poorly. In general, problems were caused by the small sample sizes and difficulties in dealing with nuisance parameters that can cause biases in estimated parameters that can also affect the performance of tests and forecasts.

The last 35 years has seen all sorts of challenges overcome in an unending search for improvement in model based estimation, testing and forecasting. Many of these developments have become feasible because of the advances in computer hardware and software during that time. Also the ready availability of simulation methods have helped assess the small sample performance of proposed methods, both absolutely and comparatively. This special issue makes a contribution to this literature with the aim of bringing some of these advances to the notice of statisticians and others interested in model based statistical inference.

The main ideas behind point optimal testing plus a strategy for the general application of such tests were outlined by King [6]. This issue opens with a paper that surveys the post 1987 literature on point optimal testing with particular emphasis on dealing with nuisance parameters. That period has witnessed the development of asymptotic point optimal testing led by the pioneering work of Elliott, Rothenberg and Stock [2] and, more recently, Müller [10] with a range of applications involving unit root testing, testing for cointegration and breaks or variation in regression coefficients. The review closes with an outline of a new class of point optimal tests for multi-dimensional testing, an area with few applications to date.

Jahar Bhowmik contributes a paper that demonstrates the t-test of a classical regression coefficient is uniformly most powerful for a wider class of invariant tests. It is widely known that the F-test is uniformly most powerful within the class of tests that are invariant to four separate sets of transformations of the data. Because the t-test statistic is the square root of the classical F-test statistic, research papers and standard texts (see for example [3,8,13]) typically state that the t-test is uniformly most powerful for the same four sets of transformations as the F-test. Bhowmik

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shows that only two of the four transformations are needed for the restriction to invariant tests, and that therefore the t-test is uniformly most powerful for a wider class of tests.

The third paper on testing by Maxwell King and Shahidur Rahman involves testing random regression coefficients in the linear regression model. This is a problem for which Rahman and King [12] found marginal likelihood based tests performed well, under the assumption of normally distributed disturbances. King and Rahman's paper investigates the robustness of these tests to non-normality and finds that the conclusions of Rahman and King [12] still hold.

In the first of two papers largely concerned with estimation, Muir Mahmood extends the work of Mahmood and King [9] in studying estimating equations of disturbance parameters in the general linear regression model. Mahmood and King [9] prefer the use of estimating equations from the marginal likelihood while the current study makes the case for the use of estimating equations from the conditional profile restricted likelihood introduced by Laskar and King [7].

The late Anis Mukhopadhyay and Rabindra Das contribute a paper on inference in the log-linear regression model with composite autocorrelated errors which are the sum of white noise and first-order autoregressive errors. This error structure was first considered by Revankar [13] in the standard linear model. Mukhopadhyay and Das suggest an estimation method for this model as well as tests and confidence ellipsoids for the regression parameters.

Motivated by the need to forecast crop yields in response to different weather conditions, Ranjit Paul introduces the use of wavelet methodology for the prediction of the exogenous variable in an autoregressive integrated moving average with exogenous variable-generalized autoregressive conditional heteroscedastic (ARIMAX-GARCH) model. He compares forecasts from this ARIMAX-GARCH-WAVELET model with forecasts from ARIMAX and ARIMAX-GARCH models in the context of forecasting wheat yield in the Indian district of Uttar Pradesh. He finds the new model has a better modelling and forecasting performance than the other models.

The second forecasting paper by Farid Osman and Maxwell King is concerned with the development of exponential smoothing methods that allow for the inclusion of regressors to improve forecasting performance. In an earlier paper, Osman and King [11] extended the Holt-Winters double exponential smoothing method to include regressors as an alternative to Hyndman et al.'s [4] suggested method based on a state space approach. The current paper looks at estimation and initialization procedures for the new method as well as the restrictions that need to be imposed on the parameters in order to satisfy forecastability conditions. The paper concludes with an empirical study that involves forecasting Australian household consumption expenditure using lagged Australian household disposable income as a regressor.

The final paper in this issue by Ranjani Atukorala, Maxwell King and Sivagowry Sriananthakumar illustrates the use of the Kullback-Leibler Information measure to gauge the closeness of an approximating distribution to the true distribution. This is used to investigate how the characteristics of population distributions impact on the convergence in the central limit theorem. Simulation results are used to make recommendations on minimum sample sizes required for what the authors regards as an accurate normal approximation of the sample mean distribution for different levels of skewness and kurtosis in the population distribution.

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