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Moment matching versus Bayesian estimation: Backward-looking behaviour in a New-Keynesian baseline model

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ABSTRACT

The paper considers an elementary New-Keynesian three-equation model and compares its Bayesian estimation based on conventional priors to the results from the method of moments (MM), which seeks to match a finite set of the model-generated second moments of inflation, output and the interest rate to their empirical counterparts. It is found that in the Great Inflation (GI) period—though not quite in the Great Moderation (GM)—the two estimations imply a significantly different covariance structure. Regarding the parameters, special emphasis is placed on the degree of backward-looking behaviour in the Phillips curve. While, in line with much of the literature, it plays a minor role in the Bayesian estimations, MM yields values of the price indexation parameter close to or even at its maximal value of unity. For both GI and GM, these results are worth noticing since in (strong or, respectively, weak) contrast to the Bayesian parameters, the covariance matching thus achieved appears rather satisfactory.

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1. Introduction

The New-Keynesian modelling of dynamic stochastic general equilibrium (DSGE) with its nominal rigidities and incomplete markets is still the ruling paradigm in contemporary macroeconomics. The fundamental three-equation versions for output, inflation and the interest rate represent the so-called New Macroeconomic Consensus and, as a point of departure, are most valuable in shaping the theoretical discussion on monetary policy and other topics. Over the last decade these models have also been extensively subjected to econometric investigations, where system estimations (as opposed to single-equations estimations) gained in importance. Indeed maximum likelihood (ML) and more recently Bayesian estimations crystallized as the most popular methods and by now have become so dominant that other techniques are at risk of eking out a marginal existence.

An alternative estimation approach is given by minimum distance procedures and here, in particular, the method of moments (MM). This technique concentrates on a number of statistics, also called moments, that summarize salient features of the dynamic systems. MM seeks to identify numerical parameter values such that, as measured by a suitable loss function, these model-generated moments come as close as possible to their empirical counterparts. Besides possibly the mean values of some of the variables, the moments that are most often referred to are either impulse-response functions or autocovariance functions (of vectors of variables), which convey similar information if the same shocks are underlying.

It may now be supposed that MM and likelihood methods do not necessarily stand in marked contrast but, with the autocovariances as moments, even amount to much the same thing. To quote Ríos-Rull, Schorfheide, Fuentes-Albero, Kryshko, and Santaeulàlia-Llopis (2011, p. 18): "The likelihood function . . . peaks near parameter values for which the model-implied autocovariance function of the observables matches the sample autocovariance function as closely as possible in terms of a statistical metric. It does so by forcing each shock in the model to contribute particular autocovariance features, which in total have to mimic the sample autocovariances."[1] The statement is based on the fact that the Gaussian likelihood function of a state space model has a linear decomposition in the frequency domain. The latter involves the spectral density matrices over the Fourier frequencies of the empirical and model-generated time series, respectively, which, in essence, simply repackage the autocovariances by using sine and cosine functions as weights. Thus, the parameter estimates may be said to be "ultimately determined by the implicit weighting of the discrepancy between sample and DSGE model implied autocovariance functions . . . encoded in the likelihood function" (Ríos-Rull et al., 2011, p. 20; although the authors make no explicit reference to the connection just mentioned).[2]

In practice, however, the correspondence between MM and the Gaussian likelihood is not likely to be a perfect one. First, the theoretical connection between the time-domain and frequency-domain decomposition of the Gaussian density function is an asymptotic result, while the empirical macroeconomic time series are typically rather short. Second, the data-dependent weighting scheme in the MM loss function for the autocovariances can be somewhat different from the implicit, likelihood-implied weighting scheme.[3] A third issue is that in the aforementioned correspondence the Gaussian likelihood includes all of the Fourier frequencies and accordingly relies on all of the autocovariances up to their maximal lag. By contrast, MM estimations are only based on a limited number of lags for their autocovariances.

The choice of the moments and its limitation is actually a point that critics of MM brand as arbitrary. In this respect the philosophy of MM may be taken into account. MM is deliberately a

[1] A similar characterization is given by Schorfheide (2008, pp. 398, 402).

[2] Two papers that, after mentioning the connection, employ the frequency-domain decomposition of the Gaussian density function for their estimations are Christiano and Vigfusson (2003) and Sala (2011). Incidentally, the role of the autocovariances is more clearly seen in these papers if one compares their specification of the sample periodogram with the expressions given in, e.g., Hamilton (1994, p. 158 for the univariate case, and Section 10.4 for the multivariate case). In case the likelihood is computed with the aid of the Kalman filter, the latter also provides a general (though rather involved) algorithm for factoring the autocovariance-generating function for the observed variables; see Hamilton (1994, pp. 392ff).

[3] In particular, this may be the case when owing to singularity problems MM does not employ an asymptotically optimal weighting matrix but instead resorts to a diagonal matrix.