Tailored Multiple-block MCMC Methods for Analysis of DSGE Models

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Abstract

In this paper we develop new Markov chain Monte Carlo schemes for Bayesian estimation of DSGE models. The motivation for our work arises from some of the shortcomings of the single block random walk Metropolis Hastings (M-H) algorithm (RW-MH), the sampling method that has been used to date in this context. In our basic (TaB-MH) algorithm, the parameters of the model are randomly clustered at every iteration into an arbitrary number of blocks. Then each block is sequentially updated through an M-H step. Furthermore, the proposal density for each block is tailored to the location and curvature of the target density based on the output of a suitably formulated version of simulated annealing, following Chib and Greenberg (1994, 1995) and Chib and Ergashev (2008). We also provide an extension of this algorithm for sampling multi-modal distributions. In this version, which we refer to as the TaBMJ-MH algorithm, at a pre-specified mode jumping iteration (say every 100th), a single-block proposal is generated from one of the modal regions using a mixture proposal density, and this proposal is then accepted according to an M-H probability of move. At the non-mode jumping iterations, the draws are obtained by applying the Tab-MH algorithm. The methodological developments are completed by showing how the approach in Chib (1995) and Chib and Jeliazkov (2001) can be adapted to these sampling schemes for estimating the model marginal likelihood. We illustrate our methods with the aid of stylized problems and three DSGE models that have appeared in the literature. The first is the model in Ireland (2004) where we show that the Tab-MH algorithm is more reliable and efficient than the RW-MH algorithm. Our second example is the model in An and Schorfheide (2007). The posterior distribution in this model is more challenging to simulate on account of multiple modes. As shown by these authors, the RW-MH algorithm is unable to jump from the low modal region to the high modal region, and vice-versa. The TaBMJ-MH method, on the other hand, does not suffer from this problem and moves between the two modal regions, exploring the posterior distribution globally in an efficient manner. The

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final example is the model in Smets and Wouters (2007) that involves a 36-dimensional posterior distribution. We show that the performance of our TaB-MH algorithm is unaffected by the dimension of the posterior distribution. The sample autocorrelation functions decay to zero within 30-40 lags for most parameters. In contrast, the sampled draws from the RW-MH chain are highly persistent, exhibiting significant autocorrelation even at lags 2500 and beyond. In addition, the RW-MH does not explore the same high density regions of the posterior distribution as the TaB-MH algorithm.