Available online at www.sciencedirect.com
ScienceDirect
ELSEVIER Journal of Economic Dynamics & Control 31 (2007) 2599–2636
JOURNAL OF Economic Dynamics & Control
www.elsevier.com/locate/jedc

Methods to estimate dynamic stochastic general equilibrium models

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Received 9 December 2005; accepted 10 July 2006
Available online 15 November 2006

Abstract

This paper employs the one-sector real business cycle model as a testing ground for four different procedures to estimate dynamic stochastic general equilibrium (DSGE) models. The procedures are: (1) maximum likelihood, with and without measurement errors and incorporating priors, (2) generalized method of moments, (3) simulated method of moments, and (4) indirect inference. Monte carlo analysis is used to study the small-sample properties of these estimators and to examine the implications of misspecification, stochastic singularity, and weak identification.

JEL classification: E13; C11; C13; C15; C32

Keywords: Estimation methods; DSGE models; Stochastic singularity; Priors

1. Introduction

This paper employs the one-sector real business cycle (RBC) model as a testing ground for four different methods to estimate dynamic stochastic general equilibrium (DSGE) models. The estimation methods are maximum likelihood (ML), generalized method of moments (GMM), simulated method of moments

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doi:10.1016/j.jedc.2006.09.005

(SMM), and the indirect inference procedure proposed by Smith (1993). All these methods are standard and their asymptotic properties are well known. The goals of this paper are to describe in a pedagogical manner their application to the estimation of DSGE models, to study their small-sample properties, to compare their computational costs, and to examine the implications of weak identification and misspecification.

Monte Carlo experiments are carried out under the null hypothesis and under three possible alternatives using samples of the size typically found in empirical work. Under the null, the data generating process (DGP) and the estimated model are the same. Although all methods deliver consistent parameter estimates, weak identification, stochastic singularity, and small-sample distortion are (or should be) important considerations in their practical application. Weak identification may arise intrinsically from the model solution[1] and/or from an unfortunate choice of variables or moments to estimate the model. For example, we will see that the log likelihood function of output is flatter with respect to the discount factor than that of consumption or hours worked, and that the objective function used in indirect inference may be less locally convex than that of GMM because they focus on different moments of the data.

Stochastic singularity imposes restrictions on the variables and moments that may be used for model estimation, and on the VAR representation of artificial data generated by a DSGE model. DSGE models are singular because they use a small number of structural shocks to generate predictions about a large number of observable variables. Hence, these models predict that linear combinations of observable variables should hold without noise.[2] This prediction is not satisfied by the data and is only the result of a particular misspecification, namely that the model assumes a smaller number of shocks than are present in the real world. This paper shows that singularity affects more severely ML than moment-based methods: ML estimation is limited by the number of linearly independent variables while moment-based estimation is limited by the number of linearly independent moments. The latter is a weaker restriction because it is possible to find independent moments that incorporate information about more variables than those that are linearly independent. The use of measurement errors to sidestep stochastic singularity in the ML framework is studied here as well.

The small-sample distortion in statistical inference is primarily due to fact that the asymptotic distributions of test statistics may be different from their small-sample analogues. For example, we will see that the empirical size of the t test that the parameter takes its true value may be quite different from the nominal size because asymptotic standard errors are not always a good measure of the small-sample variability of the estimates.

[1]See Canova and Sala (2005) for an example.

[2]Strictly speaking, stochastic singularity is a feature of linearized DSGE models, but it may also have implications for the estimation of nonlinear models depending on the extent to which they differ from their linearized counterparts. For some of the econometric issues that arise in the estimation of nonlinear DSGE models, see An and Schorfheide (2005) and Fernández-Villaverde and Rubio-Ramirez (2006) in the context of ML; and Kim and Ruge-Murcia (2006) in the context of method of moments.