Chapter 1

Introduction

Dynamic stochastic general equilibrium (DSGE henceforth) models are a standard tool of modern macroeconomics. Such models are used to study the determinants of the main economic aggregates - consumption, savings, and investments, as well as to analyze alternative economic policies. Unlike the macroeconomic models used in the 1960s and the 1970s, DSGE models are based on maximizing behavior of economic agents, and deal explicitly with uncertainty and agents' expectations. These features of the models are represented by a set of parameters, known as deep parameters. Because of their increasing complexity, however, DSGE models are rarely susceptible to analytical solution, and it is typically impossible to make general statements about the predictions of a model, that would be independent from the parameter values. Where these values come form is therefore a key question when evaluating the empirical and policy relevance of macroeconomic models.

Until recently complete DSGE models were never confronted with the data directly. Instead, either reduced-form vector autoregressions or single Euler equations were estimated and used for testing particular features of the underlying economic models. This has now changed, and in the last several years there has been a remarkable growth in the research on empirical evaluation of DSGE models. Nowadays researchers routinely estimate rich micro-founded models, that until recently had to be calibrated. Unlike the reduced-form or single equation estimation methods, the full set of model parameters are being estimated in an internally-consistent fashion. This, together with the finding that empirical DSGE models can fit the data as well as model-free reduced-form vector autoregressions (VAR), has made them extremely popular in central banks and other policy-making institutions. Quite large and sophisticated DSGE models are being developed, estimated, and used for policy analysis in institutions such as the Federal Reserve Board, the European Central Bank, Bank of England, RiksBank, the Bank of Canada, and the IMF.

A question that is rarely addressed in the empirical DSGE literature is that of parameter identification. This is surprising as identifiability is a prerequisite for estimation of parameters of any structural model, and the ability to do that for fully articulated macroeconomic models is considered to be one of the main accomplishments of this line of research. That parameter identification is a potentially serious issue for DSGE models is not a new concern. Among the authors who have made this point are Sargent (1976) and Pesaran (1989). More recently Beyer and Farmer (2004) provide several examples of commonly used models that are unidentifiable. They argue that the problem is likely to be common in DSGE models.

In most empirical DSGE papers the question of parameter identification is not confronted directly. Usually, if some of the parameters are considered to be of lesser interest, and/or with potentially problematic identifiability, their values are calibrated and assumed known, instead of being estimated. Furthermore, since DSGE models are frequently estimated using Bayesian methods, potential identification problems remain hidden due to the use of priors. As a result, it is often unclear to what extent the reported estimates reflect information in the data instead of subjective beliefs or other considerations reflected in the choice of prior distribution for the parameters.

One reason why this is an important issue is that DSGE models are increasingly being used for analyzing policy-relevant questions, such as, for instance, the design of optimal monetary policy. Such analysis often hinges crucially on the values assigned to the parameters of the model. It is, therefore, important to know how informative the data is for the parameters of interest, and whether there are any benefits from estimating instead of calibrating the models we use to address policy questions.

The main objective of this dissertation is to develop a methodology for studying identification issues in DSGE models. I begin in Chapter 2 by showing that any linearized DSGE model is completely characterized by a set of cross-equation and covariance restrictions on the parameters of the reduced-form solution of the model. Taking this as a starting point, I show how these restrictions can be used to analyze the identifiability, and also estimate the parameters of such models. An important simplifying assumption I make in this chapter is that the parameters of the reduced-form are identifiable, and therefore can be estimated directly. Under that assumption, I derive conditions that are both necessary and sufficient for identification. Moreover, I show that the relationship between the reduced-form and the deep parameters can be used to estimate the latter using a two-step minimum distance procedure. Unlike other minimum-distance estimators used in the DSGE literature, the estimator is asymptotically equivalent to full information maximum likelihood estimation, and is thus efficient. I also present Monte Carlo evidence showing that the estimator has good small sample properties.

While valid for some macroeconomic models, the assumption that the parameters of the reduced-form linear state space model are identifiable is too strong for many of the models estimated in the current empirical DSGE research. It does not hold for a general unrestricted linear state space model, and while linearized DSGE models often imply a large number of zero restrictions on the reduced-form, it is frequently very difficult to determine whether those restrictions are sufficient to guarantee identifiability. For that reason an alternative approach to the question of identification is required for general DSGE models. This leads us to Chapter 3 where, building upon results from Chapter 2 I show how the Information matrix for any linearized DSGE model can be evaluated analytically. Non-singularity of the Information matrix is a necessary and sufficient condition for identification, a result shown in Rothenberg (1971). Apart from its use for identification analysis, which I pursue in Chapter 4, the Information matrix is important for estimation and inference, both in the classical and the Bayesian tradition. For instance, the asymptotic covariance matrix of the maximum likelihood estimator is given by the inverse of the Information matrix. Similarly, Bayesian methods such as Metropolis algorithm or Importance sampler, use the Information matrix to draw from the posterior distribution.

Knowing how to compute the Information matrix allows us to determine the identifiability of the parameters of any parametric model. In Chapter 4 I use the result from Chapter 3 to study identification of a model estimated recently in Smets and Wouters (2007). That model was selected because of its prominence and influence in the empirical DSGE literature. Furthermore, many of the other models estimated in the literature have a lot of features in common with the Smets and Wouters model. Using the Information matrix approach, I determine that the parameters of the model are generally identifiable, including a parameter previously believed to be unidentified.

The non-singularity of the Information matrix only guarantees that the parameters are identifiable in the strict sense, that is, asymptotically. In practice, however, the data available for estimation are relatively short, and it is thus very important to know how strong identification is. This matters greatly for the precision of the parameters estimates, and the reliability of the standard methods for constructing confidence intervals, testing hypothesis and inference in general. When poorly identified models are estimated using Bayesian methods, the estimation results are strongly influenced by the specification of the prior distribution. It Chapter 4 I argue that much can be learned about the strength of identification, as well as the causes for identification problems, prior to taking a model to the data. Such problems arise, for instance, when different parameters play very similar roles in the model. I propose measures of the degree of similarity, and show how the problematic parameters can be determined. Applying this methodology to the Smets and Wouters model, I find that many of its parameters are very poorly identified. Finally, I estimate the model using maximum likelihood and compare the results to those reported in Smets and Wouters (2007) and obtained using Bayesian methods. The results show that the specification of the prior distribution has a strong influence on the estimation results.