How Do Existing Empirical Approaches Address the Challenges?

Frank Schorfheide
Department of Economics
University of Pennsylvania

Empirical Strategies

- Ultimate goal: reliable quantitative answers to substantive economic questions.

- This involves:

  - parameterizing the DSGE model

  - assessing model fit

  - generating quantitative predictions with the model

  - and hopefully attaching some measure of uncertainty / reliability to the predictions

Empirical Strategies - A Non-Exhaustive List

- Kydland and Prescott (Econometrica 1982, Journal of Economic Perspective 1996)-style calibration.

- Generalized Method of Moments (Hansen, Econometric 1982) estimation of Euler equations, etc.

- Minimum-distance estimation: minimize the discrepancy between VAR and DSGE impulse responses (e.g. Christiano, Eichenbaum, and Evans, Journal of Political Economy 2005).

- Maximum likelihood estimation (e.g. Leeper and Sims, NBER Macro Annual 1994)

- Bayesian inference (e.g. Schorfheide, Journal of Applied Econometrics 2000)

Calibration - How does it Work?

- Specify a collection of empirical regularities ("stylized facts") that the model is supposed to account for.

- Parameterization (or calibration) step: choose parameters of the DSGE model to match a subset of the "stylized facts."

- Validation: conditional on the parameterization, verify whether the model can account for the remaining "stylized facts," not used in the calibration step. If yes, model is considered "credible" to answer quantitative question of interest.

- Conduct robustness checks.

Calibration

- Takes potential model misspecification seriously - model is not viewed as "data generating process." Model is not assumed to capture all aspects of the data.
- The approach does not attach any probabilistic measures of uncertainty to the quantitative statements that it generates. We have to rely on judgements based on the validation step and the robustness check.
- The approach tends to ignore traditional measures of time series fit.
- In bad incarnations of this approach, researchers do not distinguish between stylized facts used for calibration and validation.
- The choice of stylized facts that the model is supposed to account for is often not well motivated and somewhat arbitrary.

GMM Inference - How does it Work?

- Derive moment conditions of the form $I\!E[g(y_t, \theta_0)] = 0$ from the DSGE model.
- Form sample analogs of moment conditions and, roughly speaking, choose parameters to set sample moment conditions to zero.
- Fully developed econometric framework that provides us with inference methods for θ_0 as well as specification tests.

GMM Inference

- Robust to certain types of misspecification: no probabilistic assumptions for the exogenous processes needed; we can estimate the parameters of the household's utility function (use Euler equation) without explicitly specifying the production side of the economy.

- However, if we only specify the consumption side of the model, many interesting and important questions cannot be answered with the model.

- Fairly easy to implement, because it does not require us to solve for the equilibrium in the model economy. But choice of moment conditions and weighting scheme typically matters.

GMM Inference

- Identification problems tend to be more pronounced, since the estimation ignores many of the cross-coefficient restrictions that arise when we solve the model. There is a large literature on "weak identification" but these methods are rarely used in macroeconomic applications.

- Once we have estimated all the coefficients of the DSGE model and our model passed the GMM specification tests, there is no guarantee that once we specify a probability distribution for the exogenous processes, we are able to track the historical time series.

Minimum Distance Approaches – How do they Work?

- There are many incarnations, but this one is the most widely used implementation...
- Estimate a VAR, impose an identification scheme for, say, a monetary policy shock.
- The identification scheme should be "model consistent:" if we generate data from a DSGE model, estimate a VAR, apply the identification scheme, we should be able to recover the shocks that were used when generating the data.
- Derive DSGE model responses as a function of the structural parameter.
- Estimate DSGE model parameters by minimizing discrepancy between DSGE model and VAR responses.

Minimum Distance Approaches

- Assessing the DSGE model: can the theoretical model replicate the response to a monetary policy shock?

- Addressing misspecification issues: don't use likelihood because we false assumptions about other shocks could contaminate the estimation results.

- Identification: one uses less information than, say, in a maximum likelihood approach, which amplifies identification problems. Monetary policy shocks explain only 5-10 percent of the variation in output. Other shocks might be much more informative about propagation mechanism.

- How should we weight the impulse response discrepancies (economic versus statistical weights)?

Minimum Distance Approaches

- The procedure provides no measure of overall time series fit for the DSGE model.
- Do we really know the effects of a monetary policy shock?
- One could replace impulse response functions by, for instance, autocovariance functions (Smith, Journal of Applied Econometrics, 1993)

Maximum Likelihood Estimation – How does it Work?

- Derive the likelihood function for the DSGE model.
- Maximize likelihood with respect to parameters.
- Fully developed econometric framework that provides us with inference methods for θ_0 as well as specification tests.
- Unlike the GMM approach, likelihood-based estimation requires that we specify a probability distribution for the exogenous shocks, and that we solve the model each time we evaluate the likelihood function.

Maximum Likelihood Estimation

- Takes probability distribution generated by the DSGE model very seriously.
- Maximum likelihood estimation works well if the misspecification of the DSGE model is small. However, likelihood-based analysis is potentially very sensitive to misspecification.
- If there is a lack of identification, the likelihood function will be flat in certain directions.
- In practice, likelihood function tends to be multi-modal, difficult to maximize, and often peaks in regions of the parameter space in which the model is hard to interpret.
- To cope with the practical problems, researchers often fix a subset of the parameters.

Bayesian Inference – How does it work?

- Treat parameters as random variables.
- Combine likelihood function with a prior density for the structural parameters.
- This prior density can contain information about parameters from other sources.
- Use Bayes Theorem to update initial beliefs about parameters by calculating a conditional distribution of the parameters given the data.
- Inference and decisions are then based on this posterior distribution.

Bayesian Inference

- Takes probability distribution generated by the DSGE model very seriously and hence is sensitive to misspecification issues.

- There is a large literature documenting optimality properties of Bayesian inference / decision procedures (under the assumption that the model universe contains a well-specified model).

Bayesian Inference

- The Bayesian approach is able to cope with some of the shortcomings of the maximum likelihood analysis...

- From a numerical perspective: the prior can be used to introduce "curvature" into objective function. Maximization of posterior is "easier" than maximization of likelihood function.

- Prior can be used to penalize parameterization under which the model is difficult to interpret, or parameterizations that are at odds with additional information from other data sets.

- Bayesian approach adds prior information that might be helpful to discriminate hypotheses. However, prior is not updated if likelihood is flat.

What's Next?

- We will proceed with Bayesian analysis of DSGE models and show how to:
  - parameterize the DSGE model
  - assess model fit
  - generate quantitative predictions with the model
  - attach some measure of uncertainty to the predictions
  - and, hopefully, generate reliable quantitative answers to substantive economic questions.
- We will then revisit the alternative empirical strategies.