Comment on “Policy Evaluation in Uncertain Economic Environments”
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This is an unusual paper for the Brookings panel because it is heavily methodological. I mention this at the outset, not to criticize the paper or Brookings, but to urge people who are serious about giving policy advice to read and study this paper, despite its methodological bent. This is a provocative paper; it provoked me to rethink how I would formulate and present policy advice. Any policy adviser who digests the paper’s central messages will make her advice better and more pertinent. In this discussion I adopt the perspective of a policy advisor—a perspective from which it’s apparent wherein the paper’s marginal product lies.

These comments are comprised of two parts. The first part reviews the substantial progress Brock, Durlauf, and West (BDW) have made toward embedding model uncertainty and policy evaluation in a decision theoretic framework. I highlight the aspects of their work that develop methods of reporting results that differ from the norm in ways that can be helpful to policy makers.

The second part points out the ways in which BDW’s current development falls short of offering a framework for policy evaluation that can be taken immediately into the briefing room. Before BDW’s methods can speak to actual policy questions, they need to be extended to confront identification and incorporate dynamics along with the kinds of strategic interactions that arise in rational expectations equilibria. The comment concludes with a discussion of some practical problems associated with communicating policy analysis that accounts for model uncertainty.

Brock, Durlauf, and West develop an approach to answer exactly the right question: how can we design good policies in the face of extreme uncertainty about how the economy works? Model uncertainty, almost everyone agrees, is important, yet it is grossly under-studied. And accounting for this kind of fundamental uncertainty is crucial for policy analysis when the social costs of basing decisions on a bad model can be very large.

One neat aspect of this approach, which the authors do not emphasize, is that it formalizes and systematizes an informal and unsystematic process that already takes place in policy institutions. Current practice in policy analysis brings many disparate models to bear on the
questions at hand. At Federal Open Market Committee (FOMC) meetings, for example, there are probably at least as many models and priors over models as there are participants. Models are combined with data in both coherent and incoherent ways. Acknowledgement of model uncertainty and a type of model averaging both take place during policy debates, as arguments frequently draw on implications from different models. Because all of this occurs informally, there is little basis for comparing competing models. And although the models are presented as competing, the rules of the competition are vaguely spelled out. At the end of the day, the “winner” is typically the model on which the policy makers base their decisions, rather than the model that most accurately represents the economy. It is also the case, unfortunately, that there is no assurance that models demonstrated to be at odds with the data will be discredited and eventually disappear.¹ BDW offer a cure for this common practice by creating a framework for rigorous discussion of alternative models.

It may be especially difficult to apply the BDW methodology to U.S. monetary policy. It is unlikely the governors and presidents of the Federal Reserve System could easily agree on a single loss function for the Fed.² But monetary policy analysis in countries that announce an explicit inflation target may readily lend itself to BDW’s approach. Indeed, by adopting the approach, and explaining it in their Inflation Reports, inflation targeting central banks could derive the benefits that a formal and systematic approach to policy making offers. That approach may also carry with it some positive externalities: accountability and transparency.

Reflecting on how actual policy making is practiced, with its explicit, though typically informal recognition of model uncertainty, one is struck by how wide is the gulf between this practice and research on policy evaluation. It is fashionable to pose optimal monetary and fiscal policy questions as Ramsey problems, which solve for the policies that select the best competitive equilibrium. Although it is understood that the optimal policies are strongly model-dependent—varying both with the frictions present in the models and the policy instruments assumed to be available³—no optimal policy analysis proceeds by first averaging across models according to their fit to data. BDW’s paper has the potential of bridging the gulf and bringing research and practice closer together.

What BDW Offer

The paper considers a potentially very large and disparate range of models and applies formal statistical evaluation to the models. Models unsupported either by the policy advisors a priori or
by the data are given little weight in the posterior density. The authors embed this statistical analysis in a decision theoretic framework for policy evaluation as a means for arriving at optimal policy rules in uncertain economic environments.

The paper contains two extended empirical examples. The first is the “backward-looking” reduced-form monetary model of Rudebusch and Svensson (1999), for which BDW compute the mapping from weights in the policy loss function to parameters of the optimal Taylor rule, after averaging across 25,600 variants of the model. Many of their findings are close to Rudebusch and Svensson’s. Assuming Rudebusch and Svensson pre-tested their specification, the similarity of results is not too surprising because BDW’s procedure down weights ill-fitting models.

I don’t think this example does justice to the richness of BDW’s approach. The variants of the models in the example are really quite close to each other and hard to distinguish empirically. Moreover, whether three or four lags of output enter the IS curve isn’t the kind of uncertainty that gets people heated at policy discussions. Neither is it the type of uncertainty that is likely to lead to very bad policy choices based on the wrong model.

Instead, the uncertainty that matters arises when one advisor points to weak inflation figures and a Federal funds rate of 1.25% to underscore worries about deflation, while another advisor cites four consecutive quarters of rapid M2 growth to argue that deflation is not even a remote concern. The models behind each piece of advice differ dramatically—probably by more than even the most distant of the 25,600 models BDW consider. But BDW’s methodology can in principle be applied to models that differ greatly.

The second example uses cross-country growth regressions to address the question: what are the effects of tariffs on growth? Three levels of uncertainty—different growth theories, different empirical proxies are used for the theories, and different assumptions about heterogeneity of the growth processes—are considered in 8192 models. Even someone who regards growth regressions as reduced forms that cannot offer clear policy advice would find this analysis fascinating. BDW show how policy makers with various kinds of preferences would interpret and act on very different statistics. An advisor must be sufficiently attuned to the policy maker’s preferences to present evidence that speaks to the policy maker’s concerns. The example also illustrates how an advocate of a particular policy choice can mine the data to find evidence to persuade policy makers of that choice.
These are important insights. And they are applicable to the current monetary policy environment. To explain its decision to leave the Federal funds rate unchanged, the FOMC released the statement: “…the probability of an unwelcome substantial fall in inflation, though minor, exceeds that of a pickup in inflation from its already low level.” Even though FOMC members claim that deflation is extremely unlikely, the ill effects are deemed sufficiently large that policy makers adopted an asymmetric policy directive. This is a case where merely reporting central tendencies, as policy advisors are wont to do, simply doesn’t address the policy makers’ concerns.

**Necessary Extensions**

BDW offers a first step toward a practical framework for policy analysis. Before I would know how to take the framework into a policy briefing, there are some extensions that need to be worked out.

The first necessary extension involves identification. Both examples the authors present are reduced-form setups in which it is unclear how to interpret the model-averaged results in terms of economic behavior. It would be instructive to work out an example in which uncertainty is concentrated in a set of “deep” parameters, $\pi$, describing preferences or technologies. The prior distribution, $p(\pi)$, over parameters would also represent the prior distribution over economic models. Reduced forms would be indexed by $\pi$. One could then proceed with model averaging and estimation to obtain the posterior density function. Model-averaged results would now be clearly interpretable, as the posterior distribution for $\pi$ is connected to well-defined economic behavior.

In this more detailed description of private behavior, we might want to take a more symmetric position on the treatment of uncertainty. In the current paper, policy makers are ignorant of the “true” model, while private agents happily inhabit the truth. In a more symmetric treatment, private agents might understand their local environment, but be uncertain about the aggregate laws of motion. At the same time, the policy authorities would entertain a wide set of possible models, just as BDW imagine.

A second important extension is dynamics. Extending the method to incorporate dynamics serves several purposes. First, it allows policy evaluation to confront the Lucas (1976) critique head on. This is generally important, but seems particularly so for the kinds of once-for-all policy choices discussed in this paper.
Second, dynamics allow the modeling of learning, both by the private sector and the policy authority. Here two possibilities offer themselves. On the one hand, it would seem that uncertainty might become less diffuse over time, as additional data alter posterior probabilities and, therefore, policy rules and private decision rules. On the other hand, there does not appear to be much evidence that this kind of convergence on models actually takes place. The introduction of model innovation would create a dynamic that prevents convergence and may generate interesting dynamics in policy choices.

Third, dynamics might lead to a description of the BDW approach for on-going policy analysis. Over time, as new policy problems arise and the economy changes, the set of relevant models will also change. How can their approach evolve as over time policy makers apply it and private agents react to its application?

Communicating with Policy Makers

By focusing on developing the methods, the authors naturally did not confront some practical issues surrounding how to get these methods into policy meetings. Several steps are involved in using BDW’s methods. First, the policy maker must buy into the notion of model uncertainty. Although policy institutions readily admit there is no single model of the economy, there is little evidence those institutions embrace the idea of juggling many, possibly quite different, representations of reality. The closest central banks come to this is the presentation of alternative scenarios in briefing materials. But these are really alternative realizations of exogenous shocks, or alternative paths of policy instruments, rather than predictions from alternative economic structures. These alternative scenarios capture one or two degrees of uncertainty, but not the fundamental uncertainty that concerns BDW.

Second, a policy advisor must get inside the policy maker’s head to try to discern the relevant loss function. This is a difficult task, as many policy makers are reluctant to reveal their preferences, or are simply unable to articulate them. But without a clear understanding of the loss function, the advisor cannot effectively address pertinent issues and present useful analysis.

Third, there is the tricky question of how to present model-averaged results. Story telling is a key aspect of policy advice. Compelling stories get retold by the policy maker when arguing his viewpoint. Model uncertainty muddies the waters and can make the story underlying a policy recommendation murky and less compelling. At present, I fear, the BDW approach is too much of a “black box” for policy makers to find it palatable.
Although it is impressive that BDW can handle a huge number of alternative models, for practical policy analysis it’s not obvious that is the most productive way to proceed. Differences of opinion about the appropriate model usually concentrate on a small handful of alternative structures. By narrowing the class of structures, the advisor can focus discussion on the fit and implications of each viewpoint, in the hope of narrowing the differences still more.
Endnotes

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1 For example, the notion that further reductions in tax rates will generate a burst of supply-side activity sufficient to raise revenues is just as alive in some circles today as it was 20-some years ago when U.S. deficits skyrocketed.

2 Of course, an individual regional Federal Reserve bank with a single decision maker could implement the approach.

3 See, for example, Schmitt-Grohe and Uribe (2000, 2001, 2002).

References


