Commentary

Monika Piazzesi

DISCUSSION

Taylor rules, or modifications of Taylor rules such as those proposed by Clarida, Galí, and Gertler (1999), provide useful tools to describe the behavior of central banks. A large literature has estimated these rules and has investigated conditions under which it may be optimal for central banks to use them. The question asked in this paper is whether these rules are also useful in the context of inflation targeting.

To estimate these rules, the paper uses a new approach. The idea is to measure expected inflation, $E_t\pi_{t+k}$, and the output gap, $E_t x_{t+k}$, with data on the central bank's own projections (where k is the horizon of the projection).[1] Not all central banks publish their own projection numbers. Those who do publish them tend to be inflation-targeters. New Zealand and the United Kingdom have started publishing them in 1997, while Sweden started doing it in 1994. The estimations in the paper suggest that projection data really help. While estimated policy rules based on actual inflation and the output gap perform poorly over the 1990s, estimated policy rules based on projection data do a lot better: insignificant coefficient estimates become significant, "wrong signs" turn around, coefficients on inflation get larger than 1, and residuals become less autocorrelated.

Some of the results are hard to interpret in terms of what they mean for the behavior of these central banks. For example, the coefficient on output is significantly different from zero for Sweden and the United Kingdom. With policy rules that are based on actual inflation or some imprecise measure of expected inflation, the coefficient on output may just be due to the fact that output forecasts future inflation. With policy rules based on central-bank projections, this argument no longer applies; the projections already contain all relevant conditioning information for predicting inflation. Therefore, the output coefficients seem to suggest that these central banks are reacting to output. But what do we conclude from this?

I am excited about the idea of looking at central bank projections and expect that we will see many papers in the future that use these data to estimate policy rules or to look at other issues. In what follows, I will discuss two reasons to be excited that are not mentioned in the paper (section 2). The first reason is practical and has to do with the usual problems of measuring inflation and the output gap. The second reason is that projections may help us in modeling learning by central banks. I will also mention other issues that could be explored with the data (section 3). At the end of my discussion, I will bring up some disadvantages associated with central bank projections (section 4). These include potential incentives of central banks to manipulate their own projection numbers. So far, the main drawback is that the data sample is short. But the good thing about samples is that they are like trees—they grow.

ADVANTAGES OF PROJECTION DATA

Practical issues

There are several practical issues associated with estimating forward-looking policy rules. It starts with simple measurement problems. What is the right measure of inflation? John Taylor has used the consumer price index and the gross national product deflator in his papers. At this conference, Andrew Levin, Fabio Natalucci, and Jeremy Piger have focused on core inflation, while Laurence Meyer has advocated the core personal consumption expenditure (PCE) deflator. What is the right measure of the output gap? At this conference, Lars

[1] Orphanides (2003) also takes this approach.

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Svensson has recommended the Kalman filter to compute the output trend as opposed to the Hodrick-Prescott filter. But even apart from these problems, it is not clear how we should be computing expected inflation, $E_t\pi_{t+k}$, and the output gap, $E_t x_{t+k}$. To compute these conditional expected values, we need to pick conditioning variables and, more generally, the dynamics of inflation, π, and the output gap, x.

Projection data offer an easy way out of all these practical issues. If a central bank publishes PCE projections, it must be because the board members closely follow the evolution of this particular price index. Similarly, the output-gap projections are based on some kind of trend calculation, and we do not need to find out how this was done exactly. The projections already condition on the re1evant variables, and there is no model to chose. If a central bank publishes projections $E_t\pi_{t+k}$ and $E_t x_{t+k}$ for different horizons, k, the only question is what horizon k to pick to estimate the policy rule. But picking k seems easy compared with the host of other problems that we run into otherwise.

Learning by Central Banks

Tom Sargent and others have argued that learning by central banks is important to understand their behavior. In a model with learning, the current belief of the central bank is a state variable. If the data we observe are generated from such a model, we are bound to find parameter instability in policy rules that are written in terms of current inflation, π_t, and the output gap, x_t. Now projection data may just be the right measure of current beliefs. If this is right, we may be able to estimate policy rules that are stable functions of the projection data.

MORE THINGS TO DO WITH PROJECTION DATA

Model Behind the Projections

It would be interesting to know what a model of the economy that gives rise to these projections would look like. In particular, it would be interesting to see whether learning is an important feature of such a model. To set up such a model, answers to the following two questions would be useful. First, what are the empirical properties of the projection data? The paper plots the data in Figures 1 and 2. The paper also computes the variances of changes in the projections in Table 3. But it would be useful to know more about the data: Are these projections unbiased? Are the projection errors autocorrelated? Can they be forecasted with lagged macroeconomic variables? How do the projections compare with forecasts from estimated autoregressive processes? How do they compare with those from estimated vector autoregressions (VARs)?

Second, how do policy rules based on projection data and on VAR forecasts compare? Clarida, Galí, and Gertler (1999) compare their forward-looking policy rule with rules based on π_t and x_t. The paper here compares policy rules based on projection data with rules based on π_t and x_t. Now it would be interesting to know how the policy rules here compare with those estimated by Clarida, Galí, and Gertler.

Financial Data and Private Information

An alternative way to measure expectations is to use financial data. I have looked at this issue in the context of a model of the term structure of interest rates, in which the Federal Reserve targets the short rate (Piazzesi, forthcoming). According to the estimated policy rule from the model, the Fed reacts to information contained in the term structure which is available right before the Federal Open Market Committee (FOMC) meeting. I document that the rule from the model performs better than Taylor-type rules, at least as a description of Fed behavior.

One reason to estimate policy rules based on yield data is that yields may be a good proxy for the conditioning information available to the central bank at the time of the policy decision. Financial data, however, only reflect public information. If private information of the central bank is important for these policy decisions, projection data may be preferable. To see whether private information matters, one could compare rules based on these two types of data.

Another interesting question would be to analyze the yield-curve implications of a model that is able to explain the projection data. If learning is part of the story, it would be exciting to see how it shows up in yields.

DISADVANTAGES

A disadvantage of projection data is that central banks have started to publish them only recently. The evidence presented in this paper is thus only based on a short sample from the 1990s. But the sample is growing, so that we will have more observations soon.

Moreover, projection numbers may not be the numbers that ultimately influence policy decisions. For example, the Fed's staff presents Green Book forecasts to the FOMC. But, of course, the FOMC has its own views about future economic developments, and its policy decisions are based on these views.

Finally, central banks may have incentives to distort their projection numbers. Such incentives may be particularly strong for inflation-targeting central banks, whose projection numbers are closely watched by the public. For these banks, inflation projections play similar roles to earnings projections by private firms. I do not know whether these incentive problems are severe, but it is certainly something to keep in mind when we interpret the results obtained with these data.

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