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Working Paper

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Working Papers, No. 12-19

Provided in Cooperation with:

Federal Reserve Bank of Boston

Suggested Citation: Fuhrer, Jeff (2013) : Real expectations: Replacing rational expectations with survey expectations in dynamic macro models, Working Papers, No. 12-19, Federal Reserve Bank of Boston, Boston, MA

This Version is available at:

<https://hdl.handle.net/10419/96422>

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Real Expectations: Replacing Rational Expectations with Survey Expectations in Dynamic Macro Models

Jeff Fuhrer

Abstract:

This paper examines the implications of changing the expectations assumption that is embedded in nearly all current macroeconomic models. The paper substitutes measured or “real” expectations for rational expectations in an array of standard macroeconomic relationships, as well as in a DSGE model. The author finds that the use of survey measures of expectations—for near-term inflation, long-term inflation, unemployment, and short-term interest rates—improves performance along a variety of dimensions. Survey expectations exhibit strong correlations to key macroeconomic variables. Those correlations may be given a structural interpretation in a DSGE context. Including survey expectations helps to identify key slope parameters in standard relationships, and eliminates the need for having lagged dependent variables in structural models that is often motivated by indexation for prices and habit formation for consumption. Including survey expectations also obviates the need for autocorrelated structural shocks in the key equations. In a head-to-head empirical test, the weight placed on the DSGE model’s rational expectations is essentially zero and the weight on survey expectations is one. The paper also discusses the modeling complications that arise once the rational expectations assumption is abandoned, and proposes methods for endogenizing survey expectations in a general equilibrium macro model.

JEL Classifications: E32, E52

Keywords: rational expectations, survey expectations, DSGE models, habit formation

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The author thanks Larry Ball, Susanto Basu, Chris Carroll, Bill Dickens, Neil Ericsson, Ben Friedman, Refet Gurkaynak, Kajal Lahiri, Giovanni Olivei, Ignacio Presno, Bob Triest, Jonathan Wright, and seminar participants at the Federal Reserve Bank of Boston, Boston College, John Hopkins University, and Harvard University for comments and suggestions.

This paper, which may be revised, is available on the web site of the Federal Reserve Bank of Boston at <http://www.bostonfed.org/economic/wp/index.htm>.

This paper presents preliminary analysis and results intended to stimulate discussion and critical comment. The views expressed herein are those of the author and do not indicate concurrence by the Federal Reserve Bank of Boston, or by the principals of the Board of Governors, or the Federal Reserve System.

This version: January 4, 2013

1. Introduction

Over the past decade, macroeconomists have converged on using dynamic stochastic general equilibrium (DSGE) models with rational expectations as the standard for macroeconomic modeling. All these models feature a prominent role for expectations—in wage- and price-setting, consumption and investment spending, and asset prices—that most economists agree is essential to constructing a realistic depiction of economic behavior. A number of authors have documented the empirical success of these DSGE models and have suggested that they should serve as useful inputs to formulating monetary and fiscal policy (see, for example, Smets and Wouters 2003 and Christiano, Eichenbaum, and Evans 2005). In the aftermath of the Great Recession, many economists are proposing augmentations to these DSGE models that may influence policies designed to mitigate bouts of financial instability.

In almost every case the expectations in these models are assumed to be rational, in the sense that all agents' expectations are assumed to equal the mathematical expectations implied by the DSGE model. Yet a body of work suggests that simple DSGE models with rational expectations demonstrate significant counterfactual implications (see for example Estrella and Fuhrer 2002, Rudd and Whelan 2005).¹ Partly in response to such criticisms, a number of authors have proposed augmentations to earlier vintages of DSGE models that better allow the models to match many of the key moments in the data. The additions of habit formation, price indexation, adjustment costs, and serially correlated shocks all fall into this category. It is important to note that the microeconomic evidence in favor of habit formation (see, for example, Dynan 2000) is mixed at best, and there is virtually no evidence in microeconomic price data of indexation. Direct evidence on the time series properties of shocks is necessarily limited. While one can easily imagine that some shocks exhibit persistence over time (shocks to energy prices are a leading example in recent years), modelers may wish to strike a better balance between allowing for some persistence in shocks and attributing too much of the business cycle fluctuations in macroeconomic data to the time series properties of unobservable shocks.

All of these augmentations, however, are conducted using the rational expectations paradigm. This paper investigates the extent to which a change in the expectations assumption can substitute for these augmentations, thus resulting in a model that retains many of the underlying structures that have been developed in recent years, but without some of the “bells and whistles”

¹ Much earlier work emphasized the unrealistic information assumptions implied by the rational expectations hypothesis. For an early and important example, see Friedman (1979).

(or, employing an astronomical analogy, “epicycles”) that have allowed the models to meet formidable empirical challenges. In an important sense, this paper follows in the line begun by John Roberts (1997) in his paper on the use of survey expectations in an estimated New Keynesian Phillips curve.² The work also complements recent work by Fuster, Hebert, and Laibson (2012) and others, who examine the implications of more realistic (or “natural”) theories of expectation formation, as well as work that incorporates learning by economic agents about aspects of their environment (see Orphanides and Williams 2005 and Adam 2005).

The approach taken here assumes that agents conduct their economic transactions within economies that are reasonably well-approximated by the underlying relationships embodied in standard DSGE models. Thus output depends on expected output and real interest rates; inflation depends on expected inflation and real output or marginal cost; and short-term interest rates are set by a monetary authority according to a forward-looking policy rule that depends on expected inflation and output relative to their targets. It is important to note that, while one typically derives the strict form of these relationships under the assumption of rational expectations, this paper’s approach adopts a more qualitative sense of these relationships. For example, if price-setters hold prices fixed for a number of periods (as the evidence from micro data suggests), and if price-setting is not synchronized across firms, then positing a Phillips curve that depends on expected costs or output over an extended horizon still holds intuitive appeal, regardless of how expectations are formed.³ In this paper, the expectations that agents form and that influence their decisionmaking (and the evolution of output, prices and interest rates) need not conform to the mathematical expectations implied by the model.

In the absence of measures of expectations, model-consistent expectations provide a theoretically satisfying and in many ways an elegant solution to the problem of unobserved expectations. But surveys now provide rather extensive data on the forecasts and expectations

² A very early paper by Lahiri and Lee (1979) explores these issues using a different set of methodologies and a (necessarily) earlier sample period. More recently, Piazzesi and Schneider (2009) have examined the usefulness of survey expectations in affine term structure models.

³ See Adam and Padula 2011 for a discussion of how one might derive a New Keynesian Phillips curve in a model with non-rational expectations. The key assumption in their paper is that individual price-setters expect no predictable revision in their or others’ forecasts for any period in the forecast horizon. For the forecast operator F , the i th forecaster’s expected revision of forecaster h from period t to $t+1$ is 0:

$$F_t^i [F_{t+1}^h [mc_{t+s}] - F_t^h [mc_{t+s}]] = 0 \quad \forall i, h, s > 0$$

If this assumption holds, then the subjective forecast of the aggregate inflation rate is a sufficient statistic for all the agents’ forecasts. In addition, this assumption is consistent with expectations that obey the law of iterated expectations, which is employed in the derivations below, without implying that expectations are rational in the conventional sense.

formed by agents in the economy. For some agents, it is unclear whether they devote significant resources to forming their expectations, and whether the measured expectations figure importantly in their economic decisions; this may be especially true for some household expectations. But in other cases, such as the Survey of Professional Forecasters employed in this paper, forecasting is a primary business line for the survey participants, so presumably the incentives are strong for devoting significant resources to forecasting.⁴ The paper will examine evidence bearing on the question of whether these expectations appear to feed into the economic decisions made by agents participating in the economy. It will not test the extent to which survey expectations may be considered “rational” in the statistical senses of unbiased and efficient; many authors have done so in previous work (see Batchelor 1986, Bryan and Gavin 1986, Mehra 2002, Thomas 1999, and Adam and Padula 2011). Instead, this paper will take the survey expectations as given, despite the possibility that such expectations may be characterized by irrationality.

Using this approach, the paper develops evidence that the systematic use of survey expectations—one way of implementing measured, rather than assumed expectations—offers a number of advantages over the rational expectations models. The identification of key parameters is improved, and the need for macroeconomic “epicycles” such as correlated shocks and pseudo-structural features that add lagged endogenous variables to the model is obviated. The empirical success of the survey-based DSGE model is encouraging.

Of course, such an advance comes at a cost. The beauty of the rational expectations paradigm is that it instantly answers many questions about how expectations evolve. If one is willing to specify a model, one simultaneously has specified the expectations that are consistent with the model. That beauty is lost with the introduction of survey expectations, as one can no longer “solve out” expectations in the simple way that has become standard in the DSGE literature. Choosing to use survey expectations necessitates the use of theory-based approximations and empirically-motivated compromises, examples of which will be described in more detail below. Recognizing these tradeoffs, the paper concludes that the move to employing survey-based measures of expectations represents a viable and potentially useful direction for macroeconomic modeling. Section 2 provides a simple theory example that illustrates the challenges in departing from rational expectations. Section 3 presents some single-equation evidence that suggests that a variety of survey expectations measures may be helpful in key elements of macroeconomic models. Section 4 develops a DSGE model that employs an array of survey expectations measures, is consistent with

⁴ Other incentives may also influence the behavior of economic forecasters; see, for example Batchelor and Dua 1990.

the core of extant theory, and employs methods to address some of the theoretical difficulties inherent in departing from rational expectations, as highlighted in section 1. Section 5 presents empirical results from system estimation of the model developed in section 4. Section 6 concludes.

2. An Illustrative Theory Example

Examining a simple rational expectations model will help to illustrate the issues that arise in using survey expectations to model macroeconomic behavior. The example will also clarify some of the mechanics surrounding the use of rational expectations, which may be helpful for those who do not routinely solve rational expectations models.

Consider a two-equation model that describes the evolution of inflation (π) in a manner similar to that in Calvo (1983) or Rotemberg (1983). A simple process for output (y) closes the model:

$$\begin{aligned}\pi_t &= \beta E_t \pi_{t+1} + \gamma y_t \\ y_t &= \alpha y_{t-1} + \varepsilon_t\end{aligned}\tag{2.1}$$

One can iterate equation (2.1) forward successively, substituting in future expectations of y_{t+i} as follows:

$$\begin{aligned}\pi_t &= \gamma y_t + \gamma \beta E_t y_{t+1} + \gamma \beta^2 E_t y_{t+2} + \dots + \varepsilon_t \\ &= \gamma y_t \sum_{i=0}^{\infty} (\alpha \beta)^i + \varepsilon_t\end{aligned}\tag{2.2}$$

using the definition of y given in the second equation in (2.1) to substitute for all occurrences of $E_t y_{t+i}$ as $\alpha^i y_t$, and assuming that $E_t(\varepsilon_{t+i}) = 0 \quad \forall i > 0$. Alternatively, one can solve out for the unobserved quantity $E_t \pi_{t+1}$ as a function of observed inflation and output to obtain a constrained version of equation (2.2) that is based only on observables, but maintains this equations's underlying structural form :

$$\pi_t = B z_t + \gamma y_t; z_t \equiv \begin{bmatrix} \pi_t \\ y_t \end{bmatrix}\tag{2.3}$$

The symbol B represents a row from the coefficient matrix that defines the model's restricted reduced-form solution. In this case, $B = [0 \quad b_2]$ and b_2 depends in a relatively straightforward way on the underlying structural parameters $[\beta, \gamma, \alpha]$.

Now consider the same model with survey, rather than rational, expectations; the survey expectation of inflation for period $t+1$ made in period t is denoted as $\pi_{t+1,t}^S$

$$\begin{aligned}\pi_t &= \pi_{t+1,t}^S + \gamma y_t \\ y_t &= \alpha y_{t-1} + \varepsilon_t\end{aligned}\tag{2.4}$$

In this case, it is less clear how to solve the model. On the one hand, because the survey expectations are observable, one need not “solve out” the expectations in equation (2.4) in order to pin down inflation and output. However, the model is not fully closed, as no process for $\pi_{t+1,t}^S$ is necessarily implied by equation (2.4). Should one wish to simulate the model forward in time from the arbitrary initial conditions, or examine its behavior under alternative policy assumptions, one would need to specify how the survey expectations would evolve over time.

One option for proceeding is to assume that the survey expectations for inflation may be consistently iterated forward using the equation for inflation, as is the case for rational expectations. This gets us part way towards a solution; consider the first step of iteration displayed below:

$$\begin{aligned}\pi_t &= \pi_{t+1,t}^S + \gamma y_t + \varepsilon_t \\ \pi_{t+1,t}^S &= \pi_{t+2,t}^S + \gamma y_{t+1,t}^S\end{aligned}\tag{2.5}$$

But now one needs to know the survey-based expectation for *output* in period $t+1$. If this data is available, that solves the problem for the first step of the iteration, but it should be obvious by now that the iteration continues, and one cannot use the output process in equation (2.4) to quickly solve for all future output expectations (doing so would return us to the rational expectations solution). At some point, one will run out of survey expectations for farther-forward observations, and the question of how to close the model thus remains.

So one needs a strategy for modeling survey expectations in a general equilibrium setting such as those found in fully articulated DSGE models, or even simple models such as the illustrative model described above. The modeling exercise presented below in section 4 employs a hybrid method that implies that (a) at some horizon, survey expectations converge towards the rational expectations for the model; and (b) consequently, the long-run expectation implied by the surveys will equal the model’s steady state value for that variable. Exactly how to implement this general strategy will be discussed in section 4, and will ultimately be guided by empirical considerations as well as theoretical purity.

3. Reduced-Form and Partial Equilibrium Evidence on the Usefulness of Survey Expectations

We begin by presenting a number of single-equation results linking survey expectations measures with key macroeconomic aggregates, using multivariate relationships that are similar to those that appear in standard macroeconomic models. The point is not to claim structural identification (although we may not be all that far from achieving it), but to demonstrate the strong correlations between survey variables and key macro variables in regression equations that evoke standard macroeconomic relationships. We examine the key building blocks of a simplified DSGE model: A price-setting Euler equation, an “IS” curve that is motivated by a consumption Euler equation, and a monetary policy rule that is explicitly forward-looking.

To anticipate the findings, the overarching results from this section are that survey variables enter these equations strongly, with the expected sign and magnitude; that the dependence of key equations on lagged variables is greatly diminished or entirely absent; that the estimated shocks to these equations are generally approximately *iid*, perhaps diminishing the need for incorporating structural shocks with a significant time series structure; and that the key slope parameters are reasonably well-identified, although section 4 will more rigorously pursue this last issue.

Price-Setting

Consider an inflation equation that takes a form similar to both old-style and New-Keynesian Phillips curves, and differs little from the simple model in equation (2.1) above:

$$\pi_t = \pi_{t+1,t}^s - b(U_t - U_t^*) + w^e dp_t^e + w^f dp_t^f \quad (3.1)$$

The “unforecastable revisions” assumption of Adam and Padula (2011), as noted in footnote 3, motivates the use of such an equation using survey expectations that are not necessarily rational. The survey expectation is the four-quarter change in total CPI inflation from the Survey of Professional Forecasters.⁵ Inflation is measured as 400 times the log change in the total CPI, since this is the measure to which the survey expectations refer. The estimation sample is 1983:Q1 to the present, chosen because much of the survey data are not available until the early 1980s. We employ ordinary least squares (OLS) estimation, as the survey expectations are recorded in the middle of quarter t ,

⁵ Previous studies often use this variable as a proxy for inflation expectations in such equations. The results have been replicated using the one-quarter-ahead expectation, which is available in the Survey of Professional Forecasters database and which corresponds more closely to the theory model. The results are the same in all essential respects.

and thus can only contain price and output information for quarter $t-1$ and earlier.⁶ Both the unemployment gap, measured as the difference between the civilian unemployment rate and the CBO's estimate of the NAIRU, and the two relative price variables for the log change in energy and food prices (dp^e and dp^f) enter contemporaneously and with two lags.⁷ Restricting inflation expectations to enter with a coefficient of one is a step toward a more structural equation; moreover, the p -value for the F -test of this restriction is 0.76, so it is clearly not rejected by the data. The regression results and summary statistics are reported in panel 1.1 of table 1 below. Figure 1 displays the fitted values. The results suggest a prominent role for survey expectations in the inflation equation. These results are similar to those reported in Fuhrer (2012) and Fuhrer, Olivei, and Tootell (2012).

An empirical fact that has dogged researchers for decades is the dependence of macro variables on their own lagged values, after accounting for the normal structural influences. This empirical regularity has given rise to the inclusion of rule-of-thumb pricing or indexation (Galí and Gertler 1999; Christiano, Eichenbaum, and Evans 2005) for price-setting, and to habit formation (Fuhrer 2000; Carroll and Overland 2000) for consumption models. Table 2 shows the diminished dependence of these two equations on lagged dependent variables once the survey expectations are taken into account. For the estimated Phillips curve, the coefficients on the two lags of inflation are small (0.01), and are estimated imprecisely. The inclusion of an additional lag further weakens statistical significance.

The autocorrelation of the residuals of equation (3.1), shown in the top panel of figure 2, suggests no significant autocorrelation. While this is still a somewhat reduced-form equation, it suggests little need for indexation or serially correlated markup shocks, once the survey expectations are included.

While section 4 will discuss modeling expectations in more detail, for illustrative purposes here a tentative step is taken toward modeling survey expectations as suggested in the preceding

⁶ Replicating these equations using the one-quarter lag of expectations variables preserves the conclusions presented in the paper in all essential respects.

⁷ Most of the data in this paper are real-time data—the SPF forecasts are not revised, and neither is the CPI inflation measure, the federal funds rate, or the 10-year Treasury yield. The unemployment rate has small and mostly seasonal adjustment-related revisions. The CBO's estimate of the NAIRU is not a real-time estimate. The CBO publishes quasi real-time estimates of the NAIRU back to 1991. However, from 1991 to 2009 these were updated each year only in January. Thus no real-time data are available prior to 1991, and the yearly updates create some undesirable discontinuities in the series. Replicating the key equations in table 1 suggests that the real-time series constructed using this data is dominated empirically by the current vintage of the CBO's NAIRU estimates.

section. We begin by iterating forward equation (3.1) and invoking the law of iterated expectations to obtain an expression for one-period ahead expectations⁸:

$$\pi_{t+1,t}^S = b_1 \pi_{t+2,t}^S - b_2 (U_{t+1,t}^S - U_{t+1}^*). \quad (3.2)$$

Of course, using the iterated forward version of equation (3.1) implies some conformity between the expectations process and the model's structure. How well such a formulation captures the behavior of the survey expectations will be explored in more detail in section 4's discussion of the system estimates.

The logic of equation (3.2) implies that inflation depends on a sequence of expected future unemployment gaps, regardless of how expectations are formed. If so, then a longer-term inflation expectation—here the SPF's measure of the average inflation rate expected over the next 10 years—may be used as a proxy for the sequence of expected future unemployment gaps. Thus we modify equation (3.2) by making the SPF one-year expectations dependent on the longer-run inflation expectations, $\Pi_{L,t}^S$, and on the SPF forecast of the unemployment rate one quarter forward, $U_{t+1,t}^S$, less the natural rate in the next period, U_{t+1}^* (using the CBO's estimate of the natural rate one-period ahead):

$$\pi_{t+1,t}^S = b_1 \Pi_{L,t}^S - b_2 (U_{t+1,t}^S - U_{t+1}^*). \quad (3.3)$$

The single-equation results from estimating equation (3.3) are displayed in panel 1.2 of table 1.

As the table indicates, the one-year inflation expectations exhibit very strong correlation with the longer-run expectations and with the forecast for the unemployment gap one-quarter forward. Figure 2 shows that this simple specification captures many of the important fluctuations in this variable over its history. The R^2 for the regression is 0.89.

Taken together, these two equations suggest the beginnings of a relatively coherent model for inflation. Inflation adheres to the generic form now prevalent in the literature, depending with a coefficient of one on near-term inflation expectations, and driven by a real variable whose effect is estimated with reasonable precision. Expectations in turn depend on further-out expectations of the real variable, and are anchored to the long-run inflation expectation. One might presume, as is done below, that the long-run inflation expectation is equal to the central bank's time-varying inflation goal. Thus the single-equation results point toward a structural model that can close much of the expectations loop in a way that reasonably balances theory and empirics.

⁸ More detail on deriving this equation is provided in section 4 below.

IS Curve (Unemployment)

The unemployment gap is motivated by standard consumption Euler equation-based IS curves, augmented by Blanchard and Galí's (2010) introduction of unemployment into the DSGE framework. Once again, the equation takes a form that is similar to the one found in the standard literature, with the current unemployment gap, $U_t - U_t^*$ a function of survey expectations of unemployment, $U_{t+1,t}^S$ and the real interest rate, ρ_t relative to its long-run equilibrium $\bar{\rho}$:

$$U_t - U_t^* = u^{ue}(U_{t+1,t}^S - U_{t+1}^*) + u^{\rho}(\rho_{t-1} - \bar{\rho}) \quad (3.4)$$

The natural candidate for the real interest rate is the one-period-ahead expected short-term real interest rate. However, some authors (e.g. Fuhrer and Moore 1995) have shown that a reduced-form IS curve that depends explicitly on a longer-term real interest rate achieves some empirical success. As a practical matter, it is important to acknowledge that it is often problematic to identify the real rate term in the IS curve (see Fuhrer and Rudebusch 2004). In this subsection, we examine reduced-form relationships that include either a short-term or a longer-term real rate.

In table 1, panel 1.3 displays the OLS estimation results for equation (3.4). The coefficient on the SPF unemployment gap expectation is precisely estimated at very near one, and the real interest rate is estimated with the correct sign and fairly high significance. The relatively small coefficients of 0.02–0.03 on both the 10-year real rate and the short-term real rate are not unusual for estimated IS curves.⁹

The R^2 for the regression is 0.99; the residual autocorrelations in the bottom panel of figure 2 suggest no serial correlation. The fitted values for the regression, shown in the bottom left panel of figure 1, suggest a very tight fit for the regression. A version of the model that includes a lagged unemployment gap, shown in the bottom panel of table 2, develops a small (but quite significant) coefficient. Thus while the role for lagged unemployment now is much diminished compared to the standard specifications with habit formation (the OLS estimate of 0.19 contrasts with that of 0.7–0.9 in many published estimates of the habit parameter), the reduced-form equation rejects the hypothesis that the lagged dependent variable has no influence.

⁹For many models, a 1 percentage point change in the federal funds rate is roughly equivalent to a 0.25 to 0.33 percentage point rise in the 10-year rate, so the expected ratio of these coefficients is three or four to one. See, for example, Fuhrer and Olivei (2011) for a discussion of these multipliers in a discussion of the effects of the Federal Reserve's Large-Scale Asset Purchase programs.

In section 4, we will discuss using long-term unemployment expectations to proxy for the sequence of expected future real interest rates that implicitly enters the IS curve, in a manner parallel to the Phillips curve discussion above.

Policy Rule

While the general form of the policy rule follows that of other rules estimated in the literature, it differs in two key respects: (1) the rule is forward-looking, in that the federal funds rate i_t responds to deviations of SPF *forecasts* of inflation and unemployment from their long-run values¹⁰; and (2) the long-run value for the federal funds rate equals the sum of an (assumed fixed) equilibrium real rate $\bar{\rho}$ and the SPF long-run inflation expectations. The central bank's time-varying target for inflation is equated with the SPF long-run inflation expectations. Thus the equation takes the form

$$\begin{aligned}\tilde{i}_t &= a\tilde{i}_{t-1} + (1-a)[i^\pi(\pi_{t+1,t}^S - \Pi_{L,t}^S) - i^u(U_{t+1,t}^S - U_{t+1}^*)] \\ \tilde{i}_t &\equiv i_t - (\Pi_{L,t}^S + \bar{\rho})\end{aligned}\tag{3.5}$$

The results from the OLS estimation of equation (3.5) are shown in table 1, panel 1.4. All the coefficients are estimated with correct signs and high statistical significance. Note that the long-run response coefficients for expected inflation and unemployment equal the estimated values reported in table 1 premultiplied by $\frac{1}{1-a}$, which yields 2.41 and -2.25 for the responses to inflation and unemployment, respectively.

The fit of the equation, displayed in the bottom-right panel of figure 1, is quite respectable. The estimated residuals for the equation exhibit little serial correlation, which is not surprising given the inclusion of the lagged dependent variable. While one might wish for a policy rule that does not require interest-rate smoothing, sorting out the sources of apparent interest-rate smoothing is a job for another paper.¹¹

¹⁰ This policy rule follows in the spirit of the forward-looking policy rules in Clarida, Galí, and Gertler (2000), substituting measured for rational expectations.

¹¹ A number of authors have explored possible explanations for the presence of interest-rate smoothing. One hypothesis is that for rules where the policy rate depends on current inflation and output, the lagged dependent variable proxies for the central bank's attempts to filter the information in the higher frequency data. That is, the rule with the lagged dependent variable may be rewritten as a rule without a lagged interest rate, but with geometrically declining weights on infinite lags of inflation and output, which is a crude way of filtering the signal in noisy data on the central bank's goals. This paper makes explicit use of forecasts of inflation and output that presumably filter the high-frequency noise in inflation and output but it still finds a role for the lagged policy rate, a result that suggests that there is not a compelling explanation for interest-rate smoothing.

Addressing Potential Simultaneity: Single-Equation Results

In the above Phillips curve and IS regressions, the presence of the contemporaneous unemployment gap and real interest rate raises the possibility that these OLS regressions are contaminated by classical simultaneous equations bias. In addition, although the survey expectations are collected in the middle of the current quarter, and the results are replicated with survey expectations that are collected in the previous quarter, the partial contemporaneous dating of the expectations might also lead to simultaneity bias. In section 4 the discussion of the systems approach will address this issue more fully, but this subsection presents instrumental variables estimates that partly alleviate the concern regarding simultaneity bias.

Simple instrumental variables regressions (using GMM) are estimated for these two key equations. The instrument set includes three quarterly lags each of inflation, the unemployment gap, the output gap, the federal funds rate, and the 10-year Treasury yield, as well as the change in food and energy prices for the Phillips curve regression. Thus we treat both the survey expectations and the contemporaneous values of the unemployment gap and the real interest rate as endogenous.

Table 3 presents the results of this exercise. The key results from the exercise confirm the results from the OLS regressions. The survey expectations enter with coefficients near one and with high statistical significance. The rational expectations versions of the equations often develop wrong-signed and/or insignificant coefficients for the unemployment gap and real interest rate. The size of the expected inflation coefficient in the rational expectations version of the Phillips curve is well below the expected value for the long-term interest rate, but essentially is one for the short-term interest rate version. Finally, in head-to-head comparisons (specification 3), the survey expectations (instrumented) dominate the rational expectations in these simple equations. The table suggests that identification is not perfect in either case, although the Phillips curve results are strong, but the survey expectations variables remain strong candidates for inclusion in macroeconomic models.¹²

Cointegration

One simple explanation for the high correlation between rational expectations and realizations of survey expectations is that the two series are integrated of order one, and thus these

¹² As is often the case with GMM, these results vary more than one would like when the details of the methodology are changed. Iterated GMM results differ from non-iterated results, while different choices for the weight matrix alter the estimates. Overall, one should take the results in table 3 as suggestive of an important role for survey expectations, even after taking account of the concerns over simultaneity bias.

regressions are simply uncovering a natural cointegration between a forecast and the realizations of the variable being forecasted. In this case, the exact lead-lag timing of the regression would not matter much: The exercise would be less likely to uncover an interesting dynamic macro link and more likely to reveal the general tendency for such paired series to move together at the low frequencies.

However, conventional unit root tests suggest it is extremely unlikely that the correlation between forecasts and realizations arises from a common unit root over the sample period in question, which in this case is 1982 to the present. Thus we rule out an explanation that relies on cointegration.¹³

Enhanced Identification

So far, the results presented in this section suggest that the survey expectations help identify some of the key parameters that are central to DSGE models. Figure 3 summarizes the findings from an exercise that is designed to highlight this advantage. The figure shows the estimated coefficient on the unemployment gap from obtained from rolling regressions of the Phillips curve in equation (3.1), with three different proxies for expected inflation:

1. Three quarterly lags of realized inflation;
2. The rational expectation of inflation in period $t+1$, or more precisely, the instrumented value of the inflation rate realized in period $t+1$,
3. The survey expectation of next period's inflation rate.

In all cases, the coefficient on the expected inflation term is constrained to equal one (the sum of the three lag coefficients is constrained to sum to one in the first case). The regressions that use the first and second proxies are estimated via OLS, while the third case employs a standard GMM estimator. All three are estimated on rolling 60-quarter samples from 1983:Q1 to 2011:Q3.

As the figure suggests, the model that employs survey expectations most consistently develops estimates of the unemployment gap coefficient that are correctly signed and statistically significant at conventional levels. The rational expectations model performs particularly poorly, and the old-style backward-looking Phillips curve yields intermediate results. The figure highlights the advantage afforded by survey expectations in identifying this key structural parameter.

¹³ The results for the augmented Dickey-Fuller test are very strong for the inflation and unemployment gap series, rejecting the presence of a unit root with p -values of 1 percent or smaller. ADF tests are weaker for the presence of unit roots for inflation and unemployment gap expectations. However, the results for the Elliott-Rothenberg-Stock and Ng-Perron tests are extremely strong for these series.

Together, these simple single-equation results suggest a strong empirical linkage, acting through a variety of channels, between the survey expectations and the key macro variables in a DSGE model. Including these variables helps identify the key slope parameters in these equations, and greatly reduces the dependence on lagged dependent variables and autocorrelated shocks to capture the dynamics in the data for macro variables. Still, one would be hard-pressed to claim identification on an equation-by-equation basis for all of these structural parameters using OLS. The next section addresses this concern in more detail.

4. A Structural DSGE Model with Ubiquitous Survey Expectations

The preceding section provided suggestive quasi-structural evidence that survey expectations may serve as very useful proxies for expectations in dynamic macro models. The surveys enter with plausible signs and magnitudes, aid in identifying key parameters, minimize the importance of lagged dependent variables in explaining fluctuations, and imply a limited role for complex structural shocks.

But there are two reasons why these regressions cannot claim to provide true structural identification. First, apart from the timing of the expectations variables, the equations include some contemporaneous variables which may well be subject to simultaneity bias. Stated differently, the simultaneous causation among interest rates, output, and inflation that is latent in the data cannot be identified without simultaneously estimating the policy rule (which implies causation from output and inflation to interest rates), the IS curve (which implies causation from interest rates to output), and the Phillips curve (which implies causation from output to inflation). The goal of this section is to specify a small macroeconomic model in which survey expectations play a key role in all of these relationships and to simultaneously estimate these key equations, with the aim of more confidently identifying the causal linkages among the key variables.

Second, the single equations do not solve the problem of how to close the model—that is, how to solve for future values of survey expectations, as highlighted in section 1. In this section, we propose reasonable compromises for closing the model with survey expectations, absent the convenience of solving out rational expectations using conventional methods. To some extent, the methods for closing the model will share common features. For example, we will always ensure that the model equations for survey expectations imply a gradual convergence toward the model's steady-state, with the convergence rate empirically determined. We will take guidance from the underlying theory to model expectations in a way that is broadly consistent with the theoretical model in which

they are embedded. However, due to the inherent limitations in available data, it will be impossible to be completely consistent across all facets of the model.

To preview some of this section’s results, we will see that from an empirical perspective it is relatively straightforward to adapt the key economic relationships in recent macroeconomic models to incorporate survey expectations. Modeling the expectations themselves, given a number of theoretical and data limitations, is more challenging. As a consequence, we will make some compromises in closing the expectations components of the DSGE model. These compromises are largely unavoidable given the departure from rational expectations and given data limitations. In section 5, which evaluates the model’s empirical performance, we will argue that these compromises are justified by greater empirical success in a number of key dimensions.

Price-Setting

The survey-based model for price-setting closely follows the strategy outlined in section 3. In motivating the model, we take a couple of steps back relative to the most recent DSGE models that include capital and wages, and begin with simpler formulations. This approach is adapted partly for simplicity and partly because many additions to the earlier models were made in response to the deficiencies observed in those models. Part of the goal of this paper is to determine to what extent those deficiencies arose from the assumption of rational expectations.

Under the standard assumptions underlying the Calvo formulation of sticky prices, the behavior of inflation without indexation will be defined by the difference equation,

$$\pi_t = \beta\pi_{t+1,t}^S + \lambda mc. \quad (4.1)$$

For a reasonable set of assumptions, one can show that marginal cost will be proportional to either the output gap or unemployment, so that we can equivalently write equation (4.1) as¹⁴

$$\pi_t = \beta\pi_{t+1,t}^S - \pi^u(U_t - U_t^*), \quad (4.2)$$

where π^u is a function of the standard Calvo parameters underlying λ , as well as the parameter on employment in the utility function. Our measure of inflation is the overall or “headline” CPI, which we choose because the longest-available long-dated (10-year) survey expectations measure from the SPF reports forecasts of the CPI. In order to aid in identifying key macro parameters, we allow for

¹⁴ See Blanchard and Galí (2010) for a derivation of a New Keynesian Philips curve with unemployment.

the independent effects of food and energy prices on the CPI as “supply shifters,” thus augmenting the simple Phillips curve as follows,¹⁵

$$\pi_t = \beta \pi_{t+1}^S - \pi^u (U_t - U_t^*) + w^e dp_t^e + w^f dp_t^f . \quad (4.3)$$

Apart from the inclusion of food and energy price shocks, the only substantive difference between this equation and the standard simple DSGE models is the use of survey, rather than rational, expectations.

Adam and Padula’s (2011) assumption that as of period t survey participants do not expect revisions to their own or other survey participants’ forecasts for periods $t+i$ for all $i>0$ (see footnote 3) allows use of the average expectation as a sufficient statistic for all the individual expectations, thus avoiding the need to model higher-order expectations. The assumption is also equivalent to assuming that the survey expectations “operator” S_t conforms to the law of iterated expectations, so that $S_t x_{t+i,t+1}^S = x_{t+i,t}^S$. This means that the expectation at date t of the expectation to be made in period $t+1$ is just the survey expectation made at period t for the same period.

Iterating equation (4.2) forward one period, and for the moment ignoring the effect of food and energy prices, we obtain

$$\pi_{t+1} = \beta \pi_{t+2,t+1}^S - \pi^u (U_{t+1} - U_{t+1}^*) .$$

Under the law of iterated expectations, one can then write the one-period survey-based expectation for inflation from the equation above as

$$\pi_{t+1,t}^S = \beta \pi_{t+2,t}^S - \pi^u (U_{t+1,t}^S - U_{t+1}^*) . \quad (4.4)$$

Of course, this iteration could in principle be carried forward into the infinite future. But in practice, we do not measure survey expectations into the infinite future. Thus we proceed as in section 3 and capture the spirit of this iteration, which then makes one-period-ahead expectations a function of an extended sequence of short-term unemployment gap expectations. The long sequence of expected unemployment gaps are approximated with the SPF measure of the 10-year average expected inflation rate, as this measure should embody—according to the model’s underlying logic—the appropriate sequence of short-term expectations, in a sense performing the forward iteration for us. This long-run inflation expectation will in turn be tied to the central bank’s inflation goal; we will

¹⁵ A measure of marginal cost that captured all marginal input costs would presumably include such cost shocks, but in the simple model here, in which marginal cost is proportional to employment, one cannot assume that this will be the case.

incorporate this linkage explicitly below. Thus we close this part of the model by positing the inflation expectations equation,

$$\pi_{t+1,t}^S = A^{\pi^e} \Pi_{L,t}^S - \pi^u (U_{t+1,t}^S - U_{t+1}^*) . \quad (4.5)$$

Of course, to completely close the model, we will need to solve for the survey expectations for unemployment in subsequent periods. We will tackle this issue when we discuss the IS curve below.

Energy and food prices, which enter equation (4.3), are assumed to follow simple AR processes in log changes:

$$dp_t^e = a^e dp_{t-1}^e \quad (4.6)$$

$$dp_t^f = a^f dp_{t-1}^f . \quad (4.7)$$

Long-run inflation expectations are taken as a proxy for the central bank's current inflation goal, which varies over time. In this model, the current inflation goal (and long-run inflation expectations) are assumed ultimately to converge to the fixed long-run central bank inflation target π^* . The inflation goal can deviate from its long-run target with some persistence, which we model via a partial adjustment equation with parameter γ

$$\Pi_{L,t}^S = \gamma \Pi_{L,t-1}^S + (1-\gamma) \pi^* . \quad (4.8)$$

OLS estimates of equation (4.8) imply that γ has a value of 0.95, and this value is used throughout the remainder of the paper.

IS Curve

Underlying the IS curves in most DSGE models is the simple life-cycle model of consumption, which under rational expectations and reasonable assumptions about preferences implies a linear approximation to the first-order conditions of the form,

$$c_t = \beta E_t c_{t+1} - \sigma(\rho_t - \bar{\rho}) , \quad (4.9)$$

where ρ_t and $\bar{\rho}$ are a real rate of interest and the long-run equilibrium value of that rate, respectively. The approach used in many simple models in the literature is adopted here: it is assumed that capital investment is either absent or proportional to consumption, and government spending is fixed, so that equation (4.9) may equivalently be written as an output equation by simply

substituting y_t for c_t , where y_t is understood to be the deviation of output from its equilibrium (perhaps flex-price) level. Finally, as discussed in the preceding subsection on price-setting, for simple production functions in which there is no difference between the intensive and the extensive margin of labor (i.e. we abstract from the difference between hours and employment), and in which capital input is fixed or absent, output and employment are proportional. One can thus substitute the unemployment gap for the output gap to arrive at an unemployment-based IS curve¹⁶:

$$U_t - U_t^* = u^{ue}(E_t U_{t+1} - U_{t+1}^*) + u^\rho(\rho_t - \bar{\rho}) . \quad (4.10)$$

The real interest rate here is defined as the difference between the one-year interest rate expectation and the one-year inflation expectation from the SPF. Finally, dropping the rational expectations assumption and substituting survey expectations, we obtain a first-order difference equation in the unemployment gap and the real interest rate,

$$U_t - U_t^* = u^{ue}(U_{t+1,t}^S - U_{t+1}^*) + u^\rho(\rho_t - \bar{\rho}) . \quad (4.11)$$

As with the price equation, this equation is complete given observations on the one-period ahead survey expectations for unemployment, which are collected in the SPF. However, in order to close the model, we need to posit a process for the unemployment expectation. As in the price-setting section, we iterate equation (4.11) forward one period,

$$U_{t+1} - U_{t+1}^* = u^{ue}(U_{t+2,t+1}^S - U_{t+2}^*) + u^\rho(\rho_{t+1} - \bar{\rho}) .$$

Assuming again that survey expectations may be consistently iterated forward as described above, we can use the equation above to derive an expression for the one-period-ahead expectation of the unemployment gap as of period t ,

$$U_{t+1,t}^S - U_{t+1}^* = u^{ue}(U_{t+2,t}^S - U_{t+2}^*) + u^\rho(\rho_{t+1} - \bar{\rho}) . \quad (4.12)$$

The logic of this equation parallels that of the New Keynesian Philips curve: the expected unemployment gap should be thought of as the average of a sequence of expected real interest rates. Thus we link the one-period-ahead inflation expectation to a long-term (e.g. ten-year average) unemployment expectation, which implicitly captures a sequence of short-run expectations of future real interest rates. While the SPF does not collect such a variable on a consistent basis over a long

¹⁶ We could use the more standard IS curve, which is expressed in terms of an output gap. But because it is more difficult to construct a measure of equilibrium output that is consistent with the SPF forecasts of GDP through the years, given the changes in methodology and base years, we choose the form that is expressed in terms of the unemployment gap. In contrast to GDP, the civilian unemployment rate concept has remained relatively stable over the years. By using the CBO estimate of the equilibrium unemployment rate, we have left ambiguous how close our equilibrium unemployment measure is to the flex-price equilibrium implied by the model.

sample, the Blue Chip forecast survey has done so since 1984.¹⁷ In a manner similar to the method employed for price-setting, we tie the unemployment expectation to a ten-year-average expectation,

$$U_{t+1,t}^S - U_{t+1}^* = u^{ue} (U_{L,t}^S - U_{1Y}^*) + u^\rho (\rho_{t+1} - \bar{\rho}). \quad (4.13)$$

As with the price-setting solution, we would normally impose the restriction that the longer-term expectation for the unemployment gap is tied to the model's steady-state, which will be zero for this concept.

Whereas the price sector implies that short-run expectations immediately respond to movements in the long-run inflation expectation (the central bank's inflation goal), as described in equation (4.5), short-run unemployment expectations appear to adjust more sluggishly to longer-run expectations. More precisely, the initial estimates of equation (4.13) show that the one-quarter expectations persistently deviate from the fundamentals specified in the equation. Figure 4 shows the difference between one-quarter (SPF) and long-run unemployment expectations in the Blue Chip survey. As the figure indicates, the gaps persist for quite a few years, also indicative of slow adjustment.

Thus we allow for data-determined partial adjustment towards the longer-run expectations implied by equation (4.13). Equation (4.14) specifies the partial adjustment of the short-run unemployment expectation to the longer-run expectations,¹⁸

$$U_{t+1,t}^S - U_{t+1}^* = \mu [u^{ue} (U_{L,t}^S - U_{1Y}^*) + u^\rho (\rho_t - \bar{\rho})] + (1 - \mu)(U_{t,t-1}^S - U_t^*), \quad (4.14)$$

where the parameter $(1 - \mu)$ indexes the speed of adjustment. As in the preceding section, the one-year real rate serves as a proxy for the theoretically preferred one-period real rate in both the IS curve and the equation defining one-period-ahead unemployment expectations.

Note that this partial adjustment formulation implicitly introduces lagged unemployment expectations into the determination of unemployment and unemployment expectations; equivalently, it builds some “intrinsic persistence” into the unemployment *expectations* process without introducing lags of realized unemployment.¹⁹ We will examine the importance of this partial

¹⁷ The 10-year average forecast is available beginning in March 1984, and is collected twice yearly, in March and October, thereafter. The use of this variable restricts the sample relative to the SPF, for which all observations are available by late 1982. See the data appendix for details on the construction of the quarterly series for the 10-year average unemployment expectation.

¹⁸ Initial estimation attempts that do not allow for partial adjustment experience more difficulty in identifying the key slope parameters in the IS relation, and also leave considerable unexplained variation in the unemployment expectations series.

¹⁹ See Fuhrer (2006) for a definition of the concepts of “intrinsic” and “inherited” persistence in the context of New Keynesian Phillips curves.

adjustment mechanism in section 5, specifically by testing the data’s ability to distinguish between the influence of lagged expected versus lagged realized unemployment.

Because the steady state for the unemployment gap should be zero in this simple model, we close the model by assuming that long-run unemployment expectations deviate temporarily from zero, in a manner parallel to long-run inflation expectations as defined in equation (4.8). That is,

$$U_{L,t}^S = \gamma^U U_{L,t-1}^S . \quad (4.15)$$

This approach guarantees that the survey expectations will converge to the appropriate steady state for the unemployment gap (zero) in the long run. OLS estimates of equation (4.15) imply that γ^U has a value of 0.94, and this value is imposed throughout the remainder of the paper.

Interest Rates

In many DSGE models, the appropriate real rate of interest for the IS curve is the short-term risk-free real rate of interest. This formulation implies that, with rational expectations, real activity will implicitly depend on the long-term real interest rate (achieved by iterating forward the Euler equation into the infinite future). The standard definition of the short-term real interest rate ρ_t is just the difference between the current short-term policy rate and the one-period-ahead expected inflation rate,

$$\rho_t \equiv i_t - \pi_{t+1,t}^S . \quad (4.16)$$

As in many studies, we find that identification of the IS curve is not straightforward. As in section 3’s reduced-form discussion, a long-term interest rate, defined as the difference between the 10-year Treasury yield and the maturity-matched inflation expectation, enters significantly in the IS equation. However, it is difficult to develop a theoretical motivation for such a relationship. The equation with the one-period short-term rate performs poorly—the estimated coefficients often have the wrong sign and quite large standard errors. As a practical compromise, here the real interest rate is defined as the difference between the one-year-ahead expected Treasury bill rate and the one-year-ahead expected inflation rate, or

$$\rho_t \equiv i_{1Y,t}^S - \pi_{1Y,t}^S . \quad (4.17)$$

This compromise retains the spirit of the one-period trade-off implied by the consumption Euler equation and yields considerably better empirical performance, as will be shown below.

We specify the policy rule that defines the short-term interest rate. We take the short-term interest rate to be the central bank’s policy rate, and develop a forward-looking policy rule that employs survey expectations of inflation, long-term inflation, and unemployment.

First, define the deviation of the federal funds rate, \tilde{i}_t from its long-run equilibrium as

$$\tilde{i}_t \equiv i_t - (\Pi_{L,t}^S + \bar{\rho}) . \quad (4.18)$$

We can then write a forward-looking policy rule in the policy rate deviation, allowing for interest-rate smoothing

$$\tilde{i}_t = a\tilde{i}_{t-1} + (1-a)[i^\pi(\pi_{t+1,t}^S - \Pi_{L,t}^S) - i^u(U_{t+1,t}^S - U_{t+1}^*)] . \quad (4.19)$$

Finally, the model is closed with an equation for the one-year-ahead SPF forecast for the three-month Treasury bill, $i_{1Y,t}^S$. We assume that the forecasts implied by the policy rule for the federal funds rate will provide a reasonable approximation to the SPF’s forecasts of the three-month Treasury bill rate over the next year. Thus the model’s forecast of the average short rate over the next four quarters is the rational expectation implied by the policy rule (and the rest of the model),

$$i_{1Y,t}^S = 0.25E_t(i_{t+1} + i_{t+2} + i_{t+3} + i_{t+4}) . \quad (4.20)$$

Note that in the model wherever rational expectations appear, these of course take into account the role that survey expectations play in the short-run evolution of the key variables. This assumption will necessarily change the way in which rational expectations act in the model, as compared to standard DSGE models in which all expectations are rational.

5. Parameter Estimates and Identification

Table 4 displays Bayesian (and, for comparison, OLS) estimates of all the parameters in the model, along with summary statistics for the simulated posterior distribution.²⁰ Table 4A displays information about the prior distributions assumed for each of the parameters.²¹ Figure 5 plots the associated parameter distributions, along with prior distributions, for each of the parameters.

²⁰ Standard convergence statistics suggest that all the simulated posterior distribution estimates have fully converged, both jointly and individually.

²¹ Note that the shock variances are assumed to have uninformative priors, so that the maximum likelihood estimates of the variances, which are implied by the other parameter estimates, the model, and the data, will equal the posteriors.

The system estimates generally do not differ too dramatically from the OLS estimates presented in table 1. But some differences are worth noting. The key elasticities in the Phillips and IS curves, π^u and u^p , both increase in magnitude relative to the single-equation OLS estimates. The difference is particularly striking for the Phillips curve, which is about four times the size of the OLS estimate. Still, in both cases the standard deviation of the posterior distribution is large enough to admit either OLS or Bayesian estimates.

In addition, the Bayesian estimates of the policy rule coefficients are smaller than the OLS single-equation estimates.²² Despite this, the estimates imply reasonably aggressive responses to expected inflation and unemployment gaps. The policy rule tracks the actual funds rate quite well, as shown in figure 6, which displays the in-sample fit of each of the model's key equations, at the estimated values of the posterior maximum for each parameter. The estimated autocorrelations of the structural disturbances, shown in figure 7, are quite similar to those developed in the single-equation estimates of section 3. For a model that excludes most lagged dependent variables and autocorrelated shock processes, the fit, while not an explicit estimation criterion, is quite good.

Identification is not trouble-free in this model using survey expectations. While the Phillips curve parameters are generally estimated with reasonable precision, including the parameters that govern the evolution of the inflation expectations that enter the Phillips curve, identification of the IS curve's slope is still less robust than would be ideal. For example, changing the horizon of the unemployment expectation in the equation can flip the sign of the real interest rate coefficient, which suggests that the model's ability to distinguish between the IS curve (in which one expects a negative correlation between interest rates and activity) and the policy rule (in which one expects a positive correlation) is not perfect.

Model Steady-State and Out-of-Sample Performance

As estimated, the model's steady-state deviates from the theoretical norm because the parameter $A^{\pi e}$ is allowed to deviate from one. In order to simulate the model with reasonable

²² Note that for comparability with the OLS estimates, the inflation coefficient reported in table 3 is the sum of i^{π} and the implicit unit coefficient on the long-run inflation expectation. The OLS coefficient is the long-run coefficient reported in section 2.

steady-state properties, we set $A^{\pi e}$ equal to one, so that the steady-state for the key variables is as expected, and as summarized in table 4B.²³

The model's parameters are estimated through the end of 2007, prior to the onset of the Great Recession. Figure 8 displays an out-of-sample simulation of the model, taking the prices of food and energy as exogenous, and assuming a constant 2 percent inflation target over the period. No other information is provided to the model for the simulation. As the figure suggests, the model does quite well at capturing the dynamics of inflation and the policy rate during this exceptionally turbulent period. The model fails to capture the slow recovery of unemployment, which is perhaps unsurprising given the model's skeletal depiction of the financial sector.

Tests for the Influence of Lagged Dependent Variables

For each of the three key structural equations that do not already include a lagged dependent variable (recall that the policy rule already incorporates this interest-rate smoothing feature), we first run a simple single-equation omitted variable test for the exclusion of the lagged dependent variable from the equation. The test takes the form

$$\varepsilon_t^i = \lambda y_{t-1}^i + \beta_i X_t^i + e_t, \quad (5.1)$$

where ε_t^i is the estimated structural disturbance for the inflation or unemployment gap equation, y_{t-1}^i is the lagged value of one of these variables, and the term $\beta_i X_t^i$ represents the other variables that enter the equation. The coefficient of interest is λ , and the null hypothesis is that $\hat{\lambda} = 0$, suggesting no additional role for the lagged variable. Table 5 presents the results for estimating this equation on the estimated shocks for the Phillips and IS curves.

As the table indicates, consistent with the results in section 3, the coefficient on lagged inflation in the Phillips curve is estimated to be quite small and insignificantly different from zero. The coefficient on the lagged unemployment gap in the IS curve is estimated to be small, but significantly different from zero, suggesting a quite small but possibly statistically important degree of habit formation.

A systems-based testing method allows joint estimation of the effect of lagged inflation and lagged unemployment in the key equations, along with the partial-adjustment mechanism for

²³ Note that this parameter restriction falls outside the 95th percentile of the simulated posterior distribution for $A^{\pi e}$. A Wald test of this restriction rejects it convincingly.

unemployment expectations represented in equation (4.14). This entails modifying the Phillips curve and IS equations as follows:

$$\begin{aligned}\pi_t &= \pi^L \pi_{t-1} + (1 - \pi^L) \pi_{t+1,t}^S - \pi^u (U_t - U_t^*) + w^e dp_t^e + w^f dp_t^f \\ U_t - U_t^* &= u^L (U_{t-1} - U_{t-1}^*) + (1 - u^L) (U_{t+1,t}^S - U_{t+1}^*) + u^p (\rho_t - \bar{\rho})\end{aligned}\quad (5.2)$$

and estimating the parameters π^L, u^L to assess the importance of lagged dependent variables.

Note first that the presence of the partial-adjustment term in the expected unemployment equation (4.14) bears dramatic implications for the model's success in replicating macro dynamics. Figure 9 displays the in-sample fit of the model at the estimated value of $(1 - \mu)$ and at a value that drastically reduces the importance of partial-adjustment. Importantly, the fit for both the IS curve *and* for expected unemployment deteriorates quite dramatically in the absence of error-correction.²⁴

The posterior modes of the Bayesian estimates of π^L, u^L in equations (5.2) are displayed in the top panel of table 6, along with simulated standard errors from the posterior distribution. These estimated parameter distributions suggest no role for lagged inflation and at best a small role for lagged unemployment in the model. Importantly, note that the estimated partial adjustment coefficient for unemployment expectations remains high at 0.86, with a standard error of 0.10. Figure 10 displays the economic significance of the estimated lagged unemployment coefficient u^L by simulating the model at the parameter values estimated in the top panel of table 6 (the dashed black line) and setting u^L to 0.01. As the figure indicates, the difference in the simulated values is virtually nil. As compared to the striking impact of the partial adjustment in unemployment expectations displayed in figure 9, the test and the simulation together suggest there is no economically significant role for lagged actual data in the model with survey expectations.

Overall, these findings are striking, and stronger than the single-equation tests. The simple OLS tests for omitted variables suggest at best a small role for lagged unemployment in the IS curve. The system tests also suggest a very small and economically insignificant role for lagged dependent variables in the model. But the role of lagged unemployment expectations in explaining current expectations appears critical to the model's success in explaining both expectations dynamics *and* realized unemployment dynamics. This is a key finding: What had appeared to be a strong dependence on lagged endogenous variables in DSGE models is better represented as the presence of inertia in expectations. Thus the model with survey expectations is able to distinguish clearly

²⁴ The fit is computed via a static simulation of the model over the sample indicated, taking relative food and energy prices and the long-run inflation expectation as exogenous.

between the direct effect of lagged realizations (as in habits and indexation) and the role of persistent expectations in determining output and inflation. In models with survey or “real” expectations, the former is far less important, while the latter takes on a key role.

A Rational Expectations “Horse Race”

The paper now examines a head-to-head comparison of DSGE models based on rational expectations with those based on survey expectations, similar to the exercises in Del Negro and Eusepi (2010) and Nunes (2010). A simple way to perform such a comparison is to augment the model equations (4.3) and (4.11) so that rational expectations enter with weight λ , and lagged dependent variables and survey expectations enter with weights as in equation (5.2), all of which sum to one as follows:

$$\begin{aligned}\pi_t &= \lambda E_t \pi_{t+1} + \pi^L \pi_{t-1} + (1 - \lambda - \pi^L) \pi_{t+1,t}^S - \pi^u (U_t - U_t^*) + w^e dp_t^e + w^f dp_t^f \\ U_t - U_t^* &= \lambda E_t (U_{t+1} - U_{t+1}^*) + u^L (U_{t-1} - U_{t-1}^*) + (1 - \lambda - u^L) (U_{t+1,t}^S - U_{t+1}^*) + u^\rho (\rho_t - \bar{\rho})\end{aligned}$$

Under the null hypothesis that $\lambda = 0$, the rational expectations are unimportant in the determination of the model’s key variables. As λ goes to 1 and π^L goes to 0, only the rational expectations matter, and the survey expectations (and equations that determine their evolution) are irrelevant. As $\lambda + \pi^L$ goes to 0, the weight on the survey expectations goes to 1, and similarly for the IS curve.

As shown in the bottom panel of Table 6, estimating this model over the sample period 1983:Q1-2011:Q3, we obtain a posterior maximum estimate for λ of 0.024, although the parameter is imprecisely estimated with a standard error of 0.14.²⁵ The estimated impact of lagged inflation and unemployment is 0.006 and 0.49, respectively; their standard errors are 0.1 and 0.18 respectively. The influence of lagged unemployment is diminished somewhat relative to the estimates in Table 4. But the observation on the tiny contribution of lagged unemployment in figure 10 still applies. Overall, these estimates suggest at best a small and economically insignificant role for rational expectations and lagged dependent variables in this model, once the information in survey expectations is taken into account.

Reduced-Form Models of Survey Expectations and Identification

²⁵ The parameters and standard errors are taken from the posterior density computed as described at the beginning of this section. The priors for λ, π^L, u^L are normal with mean 0.5 and standard deviation 0.2, which allows a small portion of the mass of the prior and posterior distributions to lie below zero.

Acknowledging the *ad hoc* nature of some of the modeling assumptions in section 4, one might be drawn towards more reduced-form representations of survey expectations as a simple means of closing the model. This subsection explores that option.

Instead of employing semi-structural equations for the key expectational variables in the model, $\pi_{t+1,t}^S, U_{t+1,t}^S, i_{1Y,t}^S$, simple VAR equations of the form indicated in equation (5.3) are substituted for these variables,

$$x_{t+i,t}^S = \sum_{i=1}^3 B_i X_{t-i} + e_t, \quad (5.3)$$

where $x_{t+i,t}^S$ is a survey expectation measure for one of the key model variables, and X_{t-i} is a vector of the lagged values of these variables as well as all of the non-expectations variables in the structural model.²⁶ Table 7 and figure 11 provide summaries of the results of estimating this model.

The results are significantly different from those obtained in the more structured model. The precision of the estimated parameters declines dramatically, as compared with those shown in table 4 and figure 5. But this negative result suggests a key source of identification in the modeling strategy of sections 4 and 5: imposing the mild restriction that the equations for the expectations variables take the iterated-forward form of the underlying behavioral relationships helps significantly in identifying key model parameters. Expressed differently, these results suggest that the survey expectations at least loosely conform to the structure of the model within which they have been embedded. Thus, using the information in the surveys to estimate expectational relationships that mimic the theoretical relationships helps to identify the parameters of the theoretical relationships.

6. Conclusions

The development of DSGE models has made significant progress over the past 20 years. But almost all of the published models employ rational or model-consistent expectations. This paper examines the extent to which an alternative expectations assumption can address the problems in DSGE model with identification, with the inclusion of lagged dependent variables that stands in conflict with evidence from micro data, and with an excessive reliance on highly correlated structural shocks.

This paper suggests that the improvements afforded by substituting real expectations—proxied by surveys of actual forecasts—are substantial. First, these expectations serve well as

²⁶ This approach is similar to the parameterized expectations approach taken in Marcet (1988) and den Haan and Marcet (1990).

expectations proxies in the standard linearized first-order conditions that make up DSGE models. Second, survey-based expectations essentially eliminate the need for adding *ad hoc* model features such as indexation and habit formation, both of which have, at best, limited support in the micro data. This substitution now means that there are no more lags in the Phillips curve and the IS curve! Third, using real expectations obviates the need to incorporate complex error processes into models in order to match the dynamic properties of macro data. Fourth, they perform well in a system context, allowing one to identify key parameters quite well, although it would be overly optimistic to suggest that all identification issues are solved. Fifth, in a head-to-head empirical test real expectations strongly dominate the incorporation of rational expectations into DSGE models. Sixth, the tests in section 5 suggest that all of the inertia imparted by lagged variables in previous DSGE models is better represented as some inertia in the expectations process, particularly in expectations for real activity. Finally, the paper provides some plausible ways of endogenizing survey expectations in DSGE models, straddling the somewhat uncomfortable spectrum that runs from *ad hoc* reduced-form solutions to full rational expectations.

Better understanding how survey expectations evolve, what structures drive their evolution, whether these expectations are stable across monetary regimes, how best to incorporate them into structural macroeconomic models, and precisely why the deviations of survey expectations from rational expectations matter for macroeconomic dynamics is the subject of future work.

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Data Appendix

Variable	Mnemonic	Description
Inflation	π_t	400 times the log change in the total consumer price index
Unemployment rate	U_t	Civilian unemployment rate
Natural rate	U_t^*	NAIRU estimate, Congressional Budget Office (CBO)
Energy price	dp_t^e	400 times the log change in the energy sub-index of the CPI
Food price	dp_t^f	400 times the log change in the food sub-index of the CPI
Federal funds rate	i_t	Quarterly average of monthly observations of the effective federal funds rate
10-year govt. yield	R_t	Quarterly average of monthly observations of the 10-year constant-maturity Treasury yield
Survey Expectations, Survey of Professional Forecasters (SPF)		
One-year inflation expectation	$\pi_{t+1,t}^S$	Average of the median inflation expectation over next four quarters from the SPF
Long-run inflation expectation	$\Pi_{L,t}^S$	Average of the median inflation expectation over next ten years from the SPF
One-quarter unemployment expectation	$U_{t+1,t}^S$	Median expectation of the civilian unemployment rate for the next quarter
Ten-year average unemployment expectation (less natural rate U_t^*)	$U_{L,t}^S$	Median expectation of the average civilian unemployment rate over the next ten years, from the Blue Chip forecast survey. The March observation is taken to be the estimate of the long-run expectation for the second and third quarter of each year, while the October observation is taken to be the expectation for the fourth quarter of that year and the first quarter of the next. The variable is expressed as the deviation from the CBO estimate of the natural rate U_t^* .
One-year Treasury-bill expectations	$i_{1Y,t}^S$	Median expectation of the average 3-month Treasury bill rate over the next four quarters
<p>Note: All SPF expectations (except the long-run unemployment expectations) are taken from the Philadelphia Fed website (http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/)</p> <p>Observations from 1990:Q3 to the present represent information through the middle of the second month of the quarter (mid-February, mid-May, and so on.). Thus respondents will normally have one month's data on unemployment for the current quarter, no or one month's data for the CPI (depending on the CPI release date), and one month's complete data for the Treasury bill rate. Note that the dating convention used in the paper takes the month in which the surveys are returned as the current period, and all the expectations used in the paper are for the quarters following the current quarter. The timing for surveys prior to 1990:Q3 is not certain, but the Philadelphia Fed's website suggests that it is "similar."</p>		

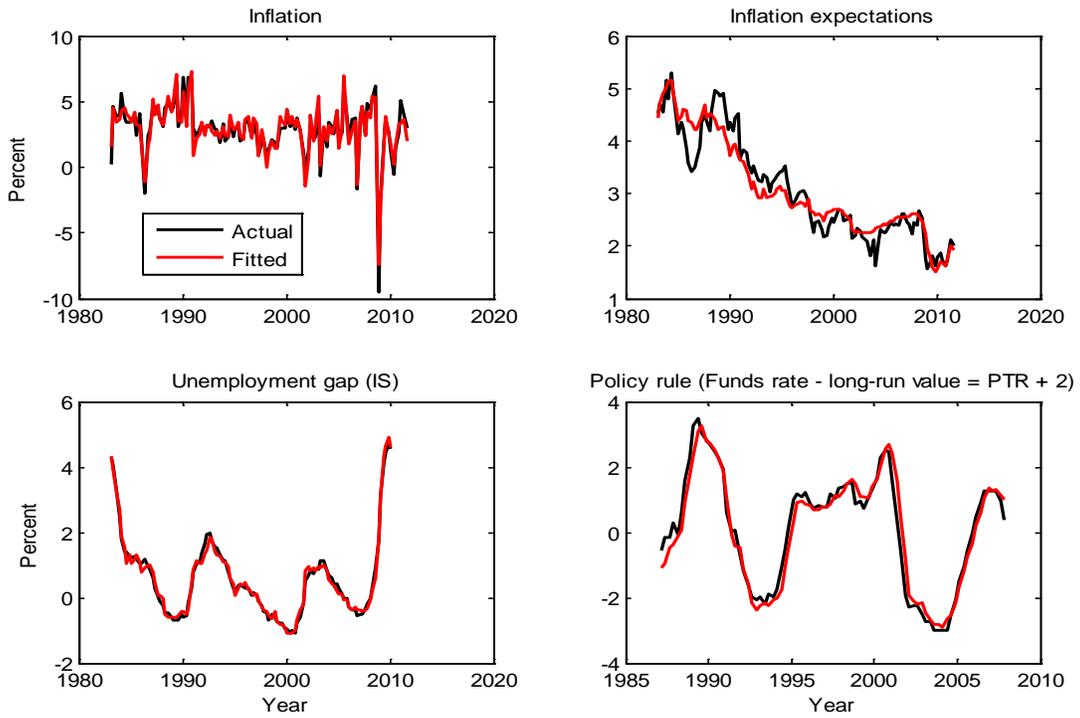
Table 1		
Regression Results, Simple Single-Equation Models		
1.1 Inflation		
Variable	Coefficient	<i>p</i> -value
Expected inflation	1	(imposed)
Unemployment gap	-0.069	0.0036
Change in food prices	0.073	0.0044
Change in energy prices	0.11	0.00
R ² : 0.89		
1.2 Inflation expectations		
Long-run inflation expectation	0.75	0.00
One-quarter-ahead unemployment expectation	-0.21	0.00
R ² : 0.89		
1.3a Unemployment gap – long rate		
One-quarter-ahead unemployment expectation	1.03	0.00
Long-term real interest rate (R10-PTR)	0.028	0.01
R ² : 0.99		
1.3a Unemployment gap – short rate		
One-quarter-ahead unemployment expectation	1.04	0.00
Short-term real interest rate ($i_{Y,t}^S - \pi_{Y,t}^S$)	0.022	0.036
R ² : 0.99		
1.4 Policy rule (Funds rate deviation)		
Lagged funds rate	0.81	0.00
SPF 4-quarter inflation expec.	0.46	0.015
SPF 1-quarter unemployment expec.	-0.43	0.000
R ² : 0.93		

Table 2		
Importance of Lagged Dependent Variables in Key Equations		
Equation	Sum of Lagged Coefficients	<i>p</i> -value
Phillips curve	0.0062	0.96
Unemployment gap (IS)	0.23	0.00

Table 3
Instrumental Variables Estimates of Key Equations

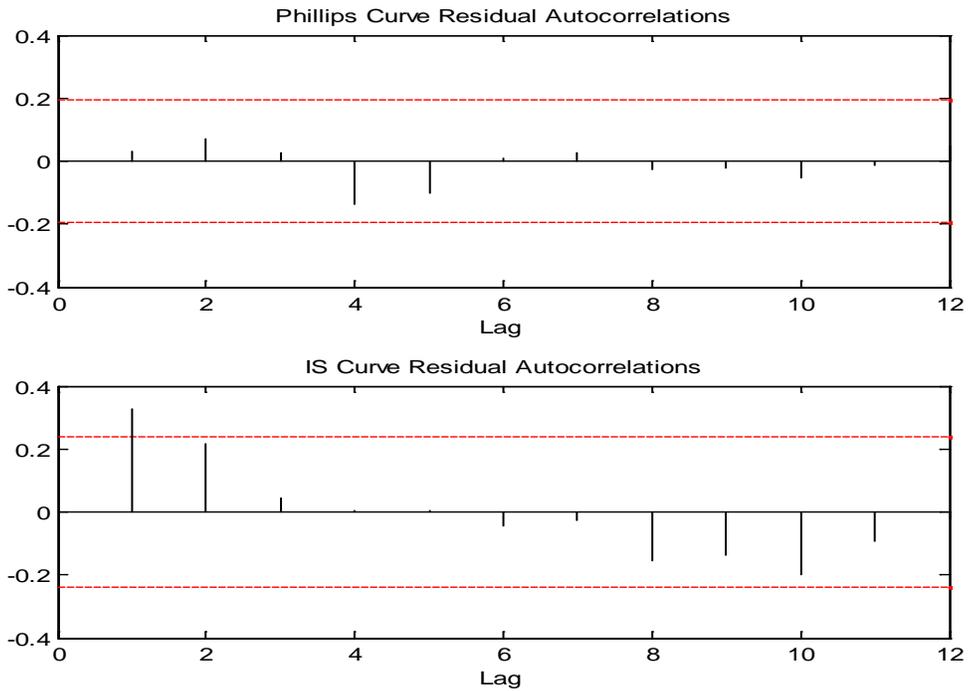
Phillips Curve				
Specification	Survey Expectation	Rational Expectation (Ex_{t+1})	Unemployment Gap	p -value, Hansen's J
1.	1.17 (0.077)	-	-0.082 (0.039)	0.92
2.	1.0 (imposed)		-0.032 (0.041)	0.92
3.	0.81 (0.069)	0.19 (0.069)	-0.11 (0.040)	0.91
4.	-	0.48 (0.12)	-0.094 (0.061)	0.85
5.	-	1.0 (imposed)	0.050 (0.074)	0.99
IS Curve: Long-Term Real Rate				
Specification	Survey Expectation	Rational Expectation (Ex_{t+1})	Real Interest Rate	p -value, Hansen's J
1.	1.05 (0.010)	-	0.0076 (0.011)	0.19
2.	1.0 (imposed)	-	0.062 (0.010)	0.64
3.	1.10 (0.11)	-0.10 (0.11)	0.058 (0.010)	0.56
4.	-	1.07 (0.022)	0.056 (0.029)	0.92
5.	-	1.0 (imposed)	-0.0042 (0.014)	0.86
IS Curve: Short-Term Real Rate				
1.	1.06 (0.011)	-	-0.0088 (0.010)	0.38
2.	1.0 (imposed)	-	-0.068 (0.011)	0.86
3.	1.04 (.067)	-0.04 (.067)	-0.073 (0.015)	0.82
4.	1.06 (0.020)	-	0.038 (0.020)	0.89
5.	1.0 (imposed)	-	-0.0036 (0.012)	0.86
Sample 1983:Q1–2011:Q3, Iterated GMM with Bartlett Kernel, Automatic Newey-West Bandwidth				

Figure 1
Fit of OLS Regressions for Key Macro Variables



Source: Author's calculations

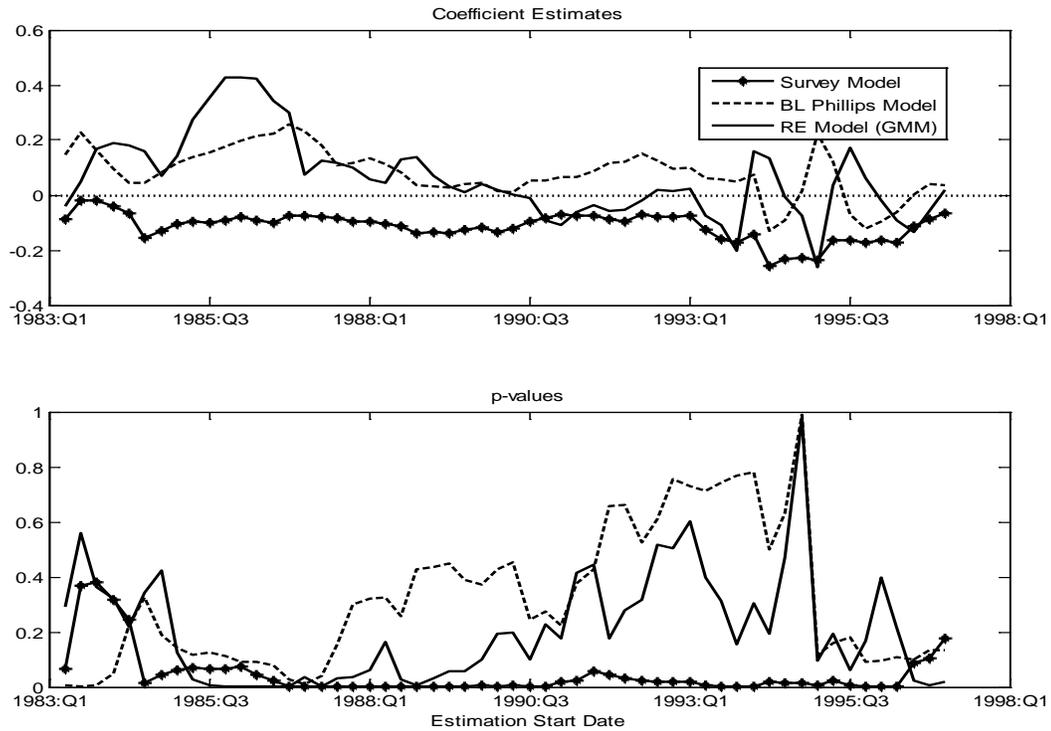
Figure 2
Autocorrelations of equation shocks



Source: Author's calculations

Figure 3

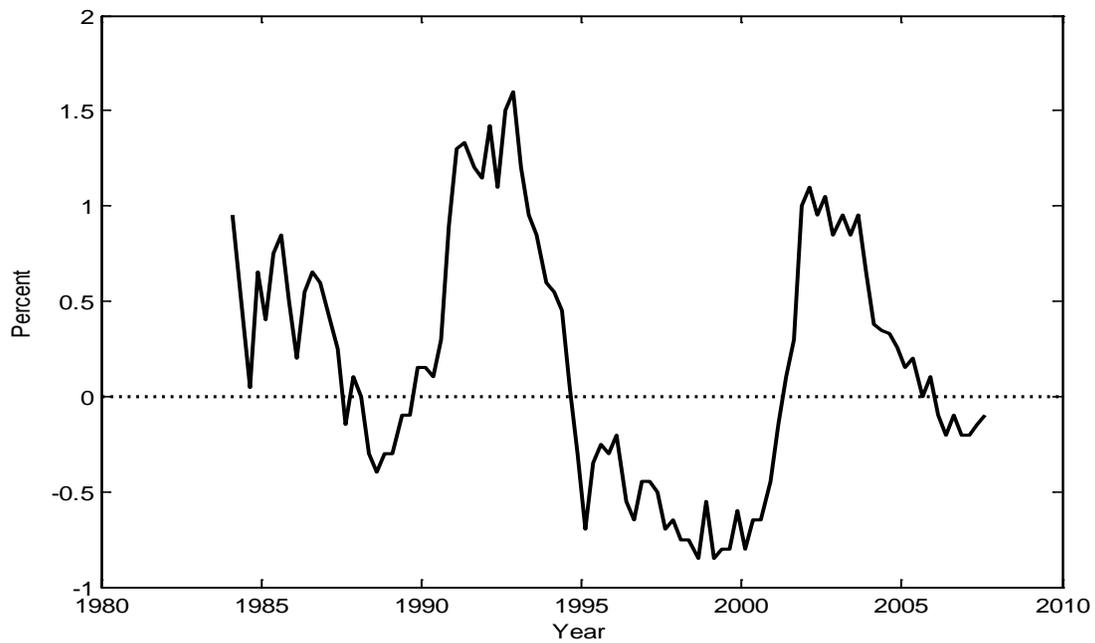
Comparison of Identification in Phillips Curve with Alternative Expectations Proxies
Unemployment Gap Coefficient, Rolling Regression Estimates, Window Size = 60
 π^e coefficients constrained to 1



Source: Author's calculations

Figure 4

Gap Between One-Quarter and Long-Run Unemployment Expectations



Source: Survey of Professional Forecasters, Blue Chip Economic Indicators

Table 4 Estimates from Simulated Posterior Distribution 1 million replications						
Posterior Distribution Summary Statistics						
Parameter	Maximum	Median	Memo: OLS	Std. Dev.	5th percentile	95th percentile
π^u	0.28	0.31	0.069	0.14	0.11	0.56
$A^{\pi e}$	0.82	0.82	0.75	0.091	0.66	0.96
u^{ue}	0.83	0.88	1.03	0.18	0.59	1.2
u^ρ	0.044	0.052	0.028	0.034	0.0082	0.12
$\bar{\rho}$	2.6	2.7	-	0.51	2.0	3.6
μ	0.13	0.14	-	0.074	0.035	0.28
a	0.87	0.86	0.81	0.082	0.7	0.97
i^π	0.89	1.0	2.4	0.33	0.5	1.6
i^u	0.28	0.54	2.3	0.33	0.12	1.2

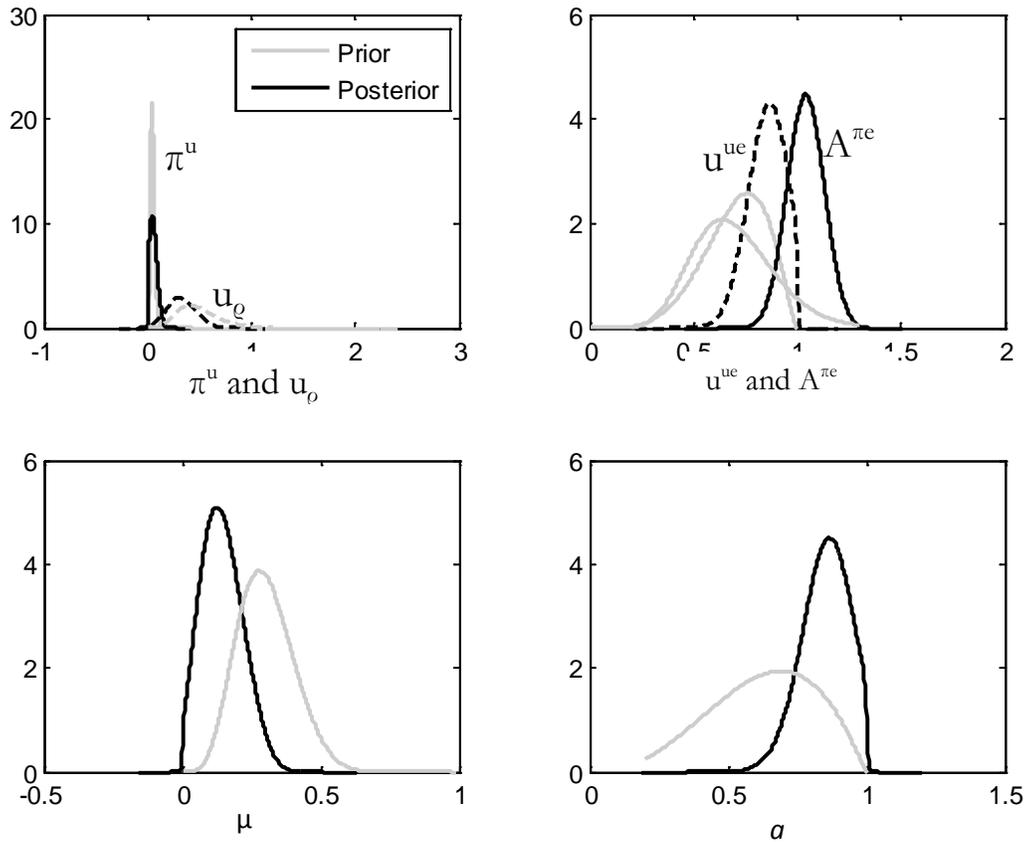
Sample: 1984:Q2–2007:Q3
Four blocks, 250,000 replications each, first 25,000 dropped for burn-in. Results for a larger burn-in allowance (100,000) are virtually identical.

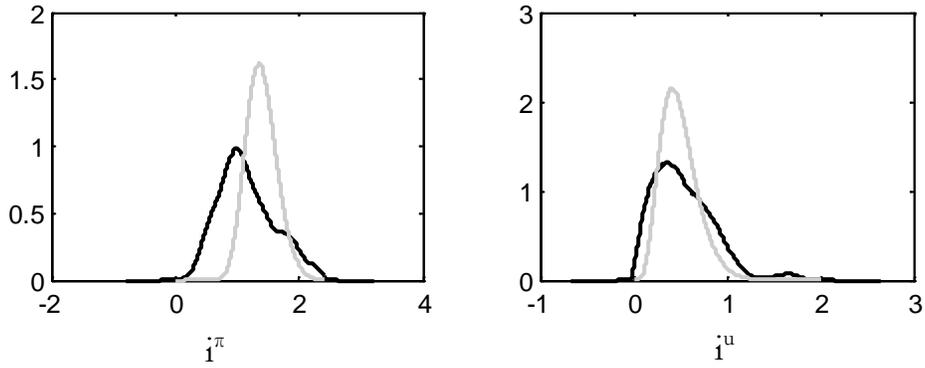
Table 4A Prior Distributions		
Parameter	Distribution	[Mean, Variance, Support]
π^u	Gamma	[0.5, 0.2, 0.001, 1.2]
$A^{\pi e}$	Beta	[0.7, 0.15, 0.001, 1]
u^{ue}	Gamma	[0.9, 0.2, 0.2, 1.3]
u^ρ	Gamma	[0.2, 0.1, 0.001, 0.5]
$\bar{\rho}$	Gamma	[2.5, 0.8, 0.001, 6]
μ	Beta	[0.3, 0.1, 0.001, 0.99]
a	Beta	[0.7, 0.15, 0.2, 1.0]
i^π	Gamma	[1.0, 0.25, 0.001, 2.4]
i^u	Gamma	[1.0, 0.25, 0.001, 3.4]
Shock variances	Uniform (non-informative)	

Table 4B Model Steady-State		
Variable	Steady State	Value at Estimates
π_t	$\Pi_{L,t}^S$	2.0
$U_{\bar{r}} - U_t^*$	0	0
dp_t^e	0	0
dp_t^f	0	0

i_t	$\bar{\rho} + \Pi_{L,t}^S$	4.6
$\pi_{t+1,t}^S$	$\Pi_{L,t}^S$	2.0
$\Pi_{L,t}^S$	π^*	2.0 (imposed)
$U_{t+1,t}^S - U_t^*$	0	0
$U_{L,t}^S - U_t^*$	0	0
$i_{1Y,t}^S$	$\bar{\rho} + \Pi_{L,t}^S$	4.6

Figure 5
Simulated Posterior Parameter Distributions
(1 million replications)





Source: Author's calculations

Figure 6
Simulated Values of Key Variables at Various Parameter Estimates 1984—2007

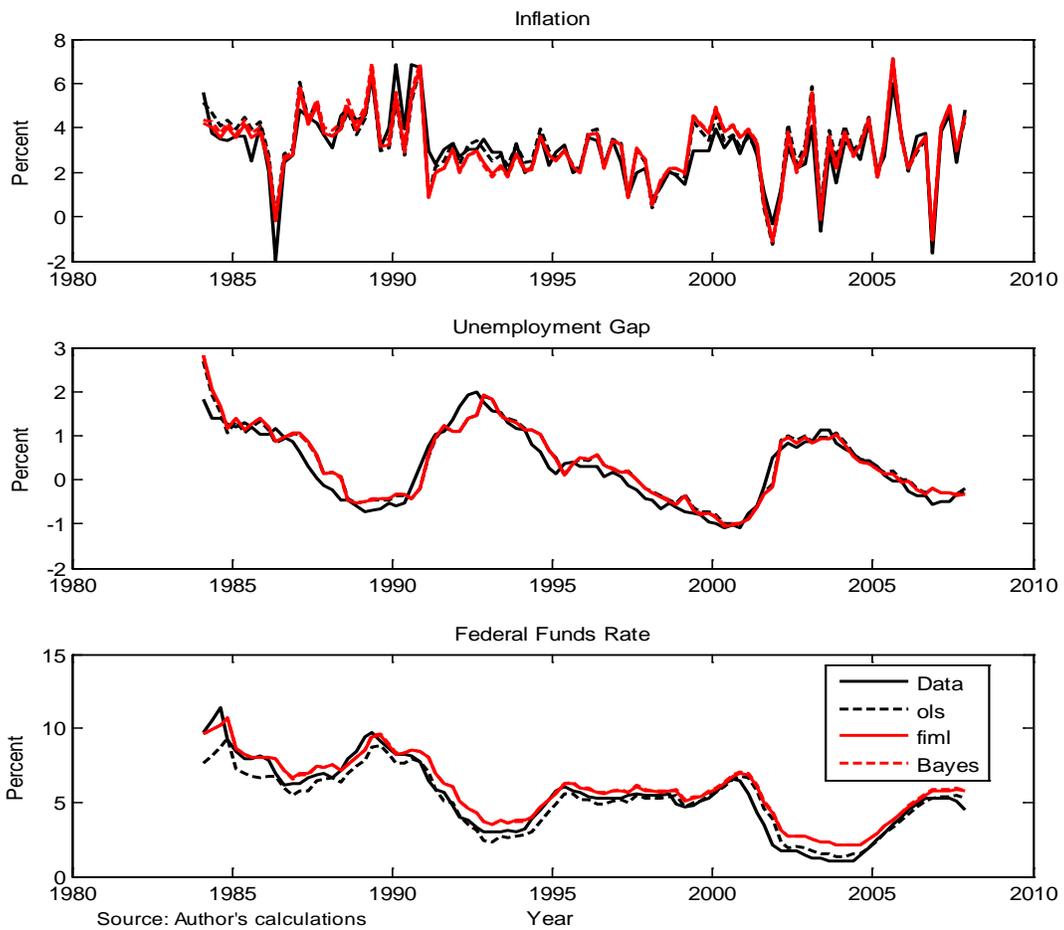


Figure 7

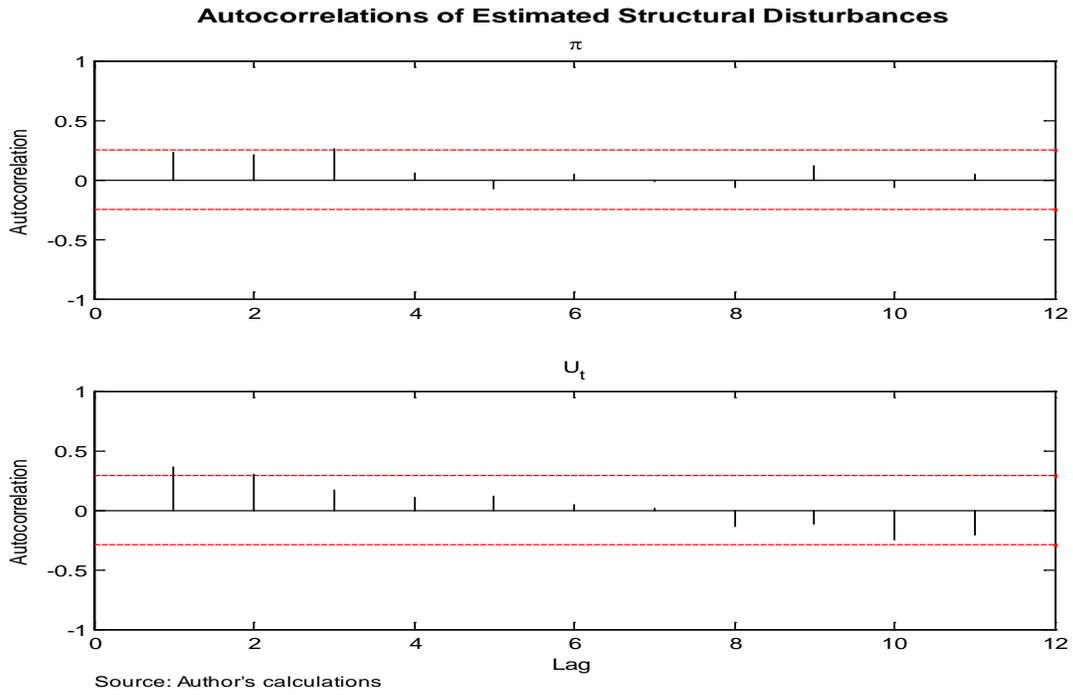
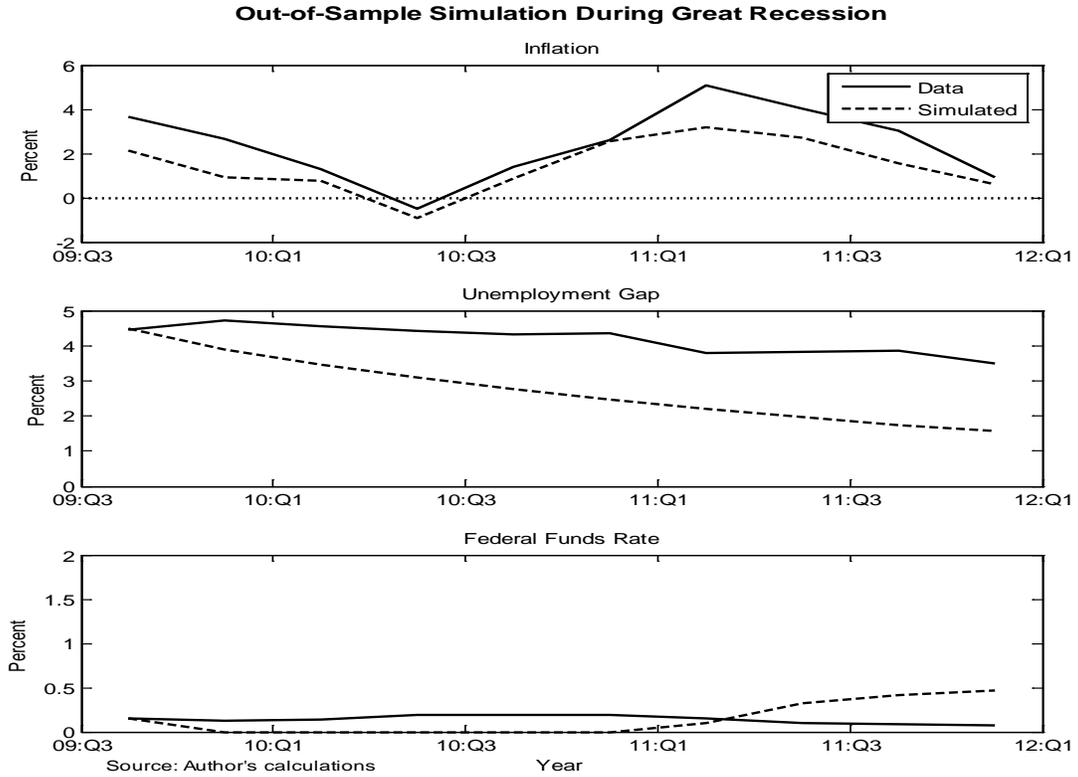


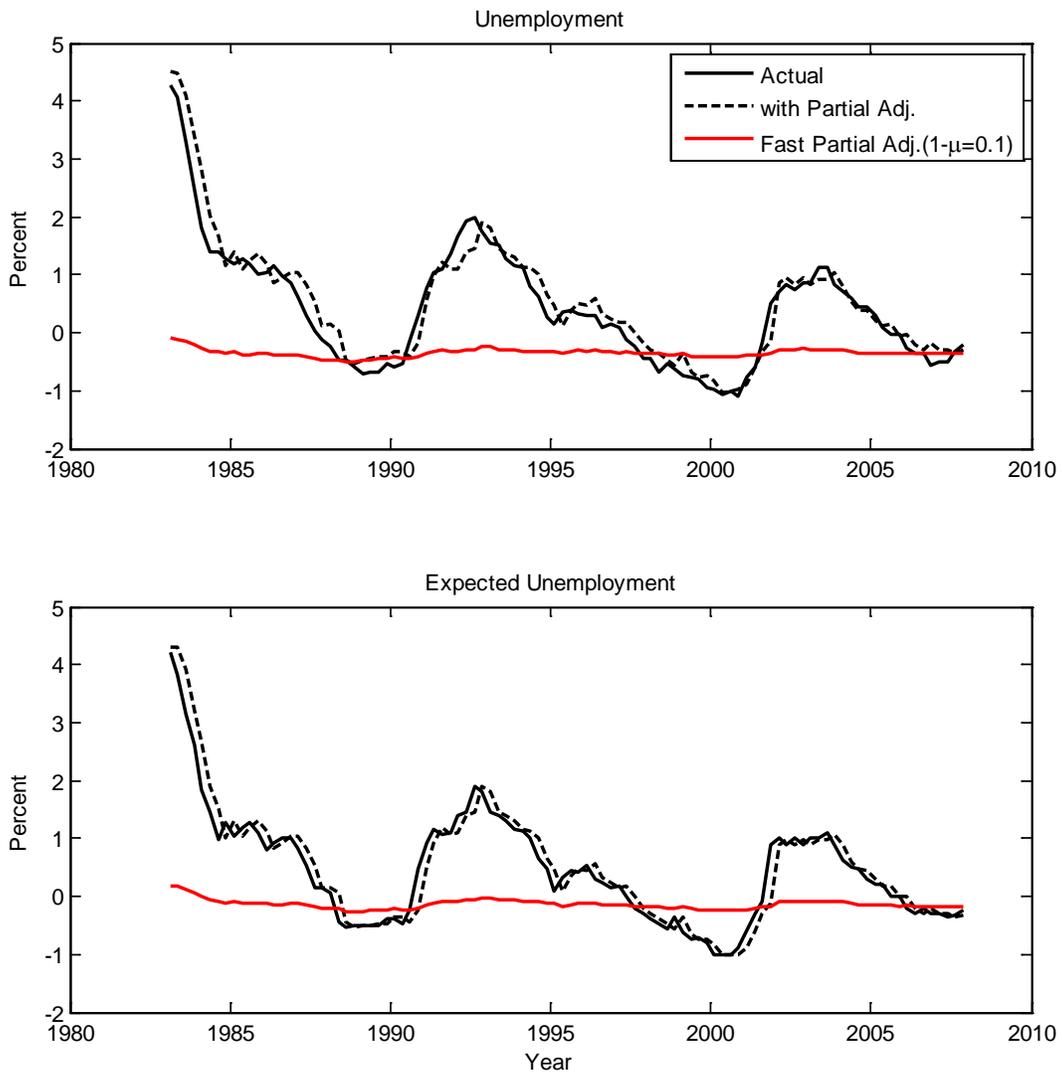
Figure 8



Equation	Lag Coefficient	<i>p</i> -value
Phillips	0.025	0.59
IS	0.28	0.00

Figure 9

**Importance of Partial Adjustment in Expected Unemployment Equation
In-Sample Fit**

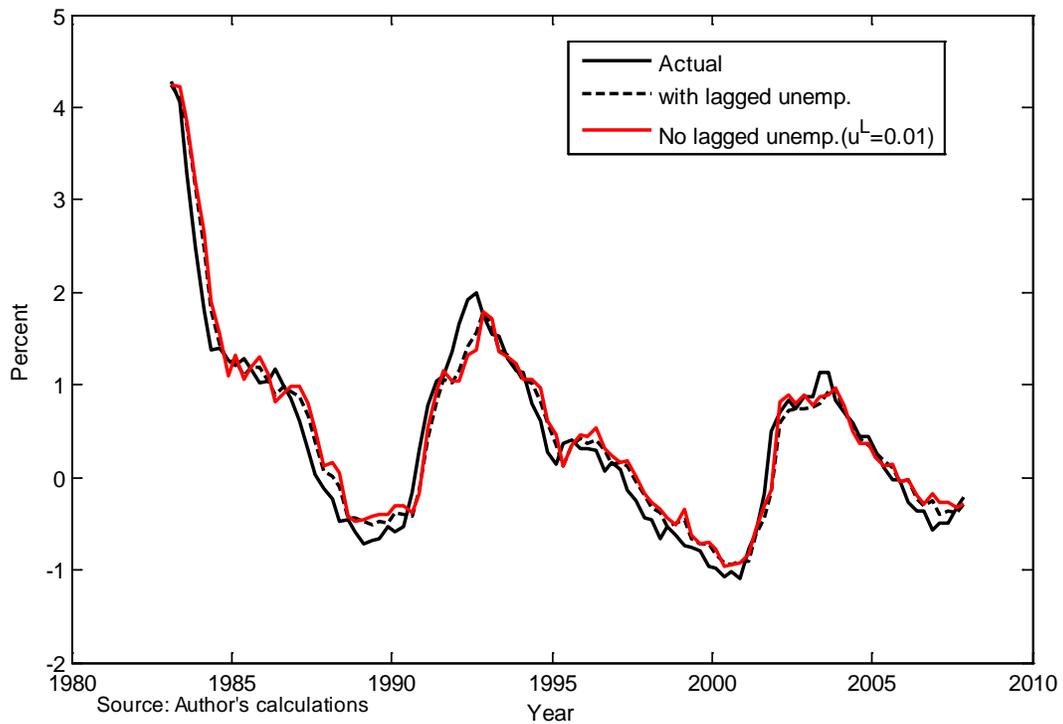


Source: Author's calculations

Table 6 System Tests		
Test for Importance of Lagged Variables		
Coefficient	Posterior maximum	Standard deviation
π^L	0.11	0.11
u^L	0.47	0.22
$(1-\mu)$	0.86	0.10
Nesting RE, Lagged Dependent Variables and Survey Expectations		
Parameter	Estimate	Standard error
λ	0.11	0.13
π^L	0.0010	0.083
u^L	0.47	0.16
$(1-\mu)$	0.86	0.089

Figure 10

Importance of Lagged Dep. Variable in Unemployment Equation
In-Sample Fit



Autocorrelation functions, with and without lagged actual, expected unemployment, or RE

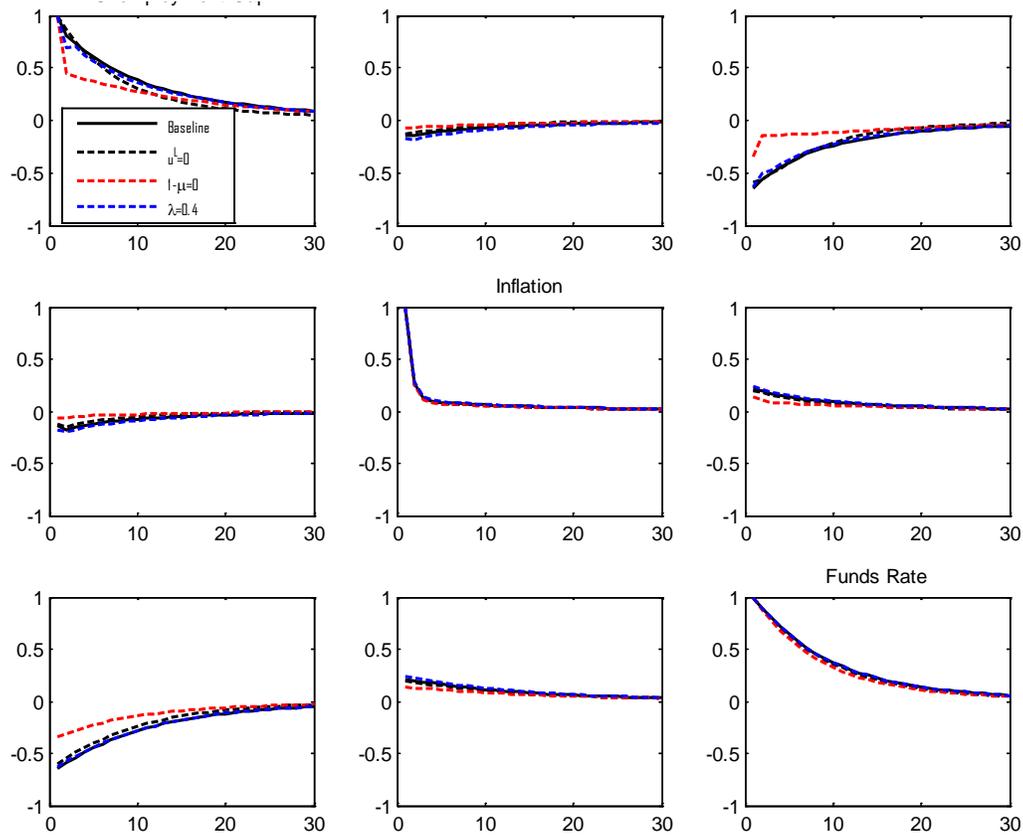
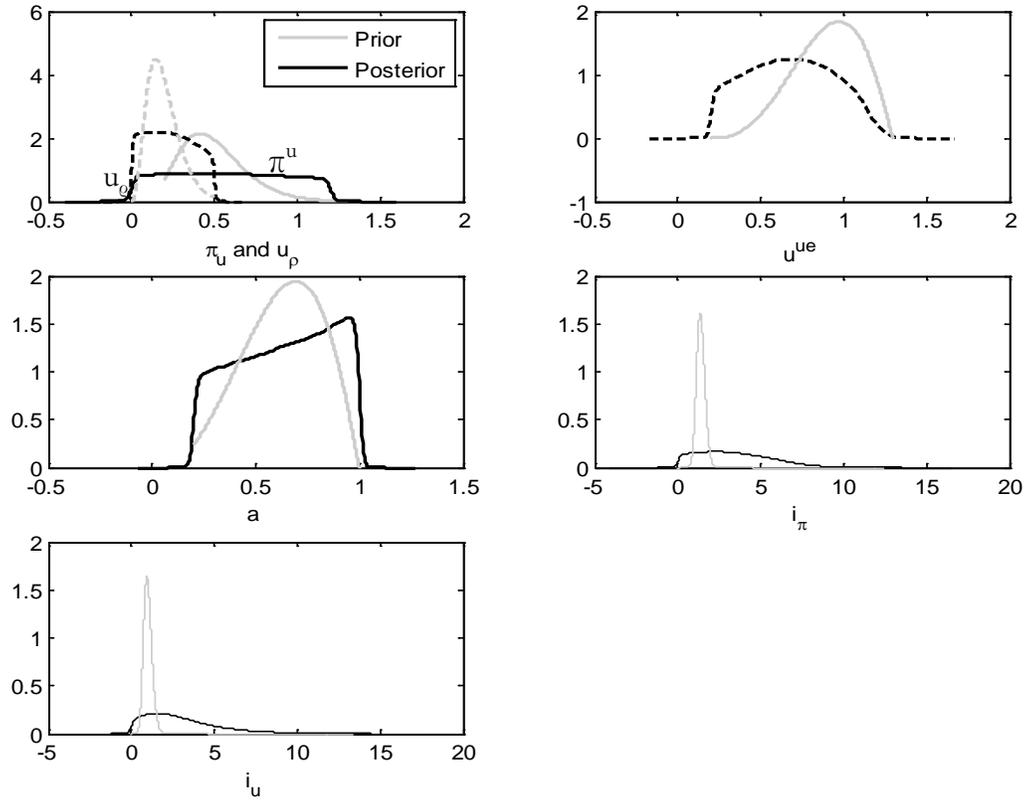


Table 7						
Estimates from Simulated Posterior Distribution						
Expectations Modeled with VAR Equations						
1 million replications						
Posterior Distribution Summary Statistics						
Parameter	Maximum	Median	Memo: OLS	Std. Dev.	5th percentile	95th percentile
π^u	0.38	0.58	0.069	0.34	0.061	1.1
u^{ue}	0.7	0.68	1.03	0.26	0.26	1.1
u^p	0.13	0.23	0.028	0.14	0.025	0.47
$\bar{\rho}$	2.5	2.8	-	1.5	0.4	5.4
a	0.95	0.65	0.81	0.23	0.25	0.97
i^π	2.2	3.2	2.4	2.2	0.37	7.5
i^u	1.6	2.6	2.3	2.3	0.32	7.5

Sample: 1987:Q1-2007:Q4
Four blocks, 250,000 replications each, first 25,000 dropped for burn-in.

Figure 11
Posterior Parameter Distributions
1,000,000 Replications



Source: Author's calculations