Real Expectations:
Replacing rational expectations with survey expectations in dynamic macro models

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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. We find 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. Inclusion of survey expectations helps to identify key slope parameters in standard relationships, and eliminates the need for lagged dependent variables in structural models (often motivated by indexation for prices and habit formation for consumption). Including surveys 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.
Introduction

Over the past decade, macroeconomists have converged on DSGE models with rational expectations as the standard for macroeconomic modeling. All of these models feature a prominent role for expectations—in wage- and price-setting, consumption and investment spending, and asset prices—a role that most economists agree is essential to a realistic description of economic behavior. A number of authors have documented the empirical success of such models (see, for example, Smets and Wouters 2003 and Christiano, Eichenbaum and Evans 2005), and suggested that they should serve as useful inputs to monetary and fiscal policy. In the aftermath of the Great Recession, authors are now proposing augmentations to these models that may influence policies designed to mitigate the effects of 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. And 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). Partly in response to such criticisms, a number of authors have proposed augmentations to earlier vintages of DSGE models that 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 are conducted under the rational expectations paradigm. This paper investigates the extent to which a change in the expectations assumption can substitute for these augmentations, leaving a model that retains many of the underlying structures that have been developed in recent years, but without some of the “bells and whistles” (or, employing an

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1 Much earlier work emphasized the unrealistic information assumptions implied by the rational expectations hypothesis. For an early and important example, see Friedman (1979).
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 (2011) 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 Orphandies and Williams 2004 and Adam 2005).

The approach taken here assumes that agents conduct their economic business within economies that are reasonably well-approximated by the 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, we adapt here 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 decision-making (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 consistent and in many ways elegant solution to the problem of unobserved expectations. But we now have rather extensive data on the forecasts and expectations formed by agents in the economy. For some agents, it is unclear whether they devote significant resources to

\(^2\) 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, Monika Piazzesi and Martin 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 \(\hat{F}_t\), the ith forecaster’s expected revision of forecast \(b\) from period \(t\) to \(t+1\) is 0:

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

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.
forming their expectations, or 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. The paper will examine evidence bearing on the question of whether these expectations appear to feed into economic decisions. The paper 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, it will take the survey expectations as given, despite the possibility of irrationality or near-rationality.

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. 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. One can no longer “solve out” expectations in the simple way that has become standard in the literature, and this necessitates the use of theory-based approximations and empirically-motivated compromises, examples of which will be described in more detail below. The paper will conclude that, recognizing these trade-offs, the move to survey-based measures of expectations represents a viable and potentially useful direction for macroeconomic modeling. Section 1 provides a simple theory example that illustrates the challenges in departing from rational expectations. Section 2 presents some single-equation evidence that suggests that a variety of survey expectations measures may be helpful in key elements of macroeconomic models. Section 3 develops a DSGE model that employs an array of survey expectations measures, is consistent with 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 4 presents empirical results from system estimation of the model developed in section 3. Section 5 concludes.
Equation Section (Next)

1. **An illustrative theory example**

We consider a simple model with expectations that 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 solve rational expectations models routinely.

Consider a two-equation model that describes the evolution of inflation ($\pi$) in a manner similar to that in Calvo (1983) or Rotemberg (1982). A simple process for output ($y$) closes the model:

$$
\pi_t = \beta E_t \pi_{t+1} + \gamma y_t \\
y_t = \alpha y_{t-1} + \varepsilon_t
$$

(1.1)

One can iterate equation (1.1) forward successively, substituting in future expectations of $y_{t+i}$ as follows:

$$
\pi_t = \gamma y_t + \gamma \beta E_t y_{t+1} + \gamma \beta^2 E_t y_{t+2} + \ldots + \varepsilon_t \\
= \gamma y_t \sum_{i=0}^{\infty} (\alpha \beta)^i + \varepsilon_t
$$

(1.2)

using the definition of $y$ given in the second equation in (1.1) to substitute for all occurrences of $E_t y_{t+i}$ as $\alpha^i y_t$, and assuming that $E_t (\varepsilon_{t+i}) = 0 \ \forall i > 0$. 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 (1.1) that is based only on observables, but maintains the underlying structural form of (1.1)

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

(1.3)

$B$ is a row from the coefficient matrix that defines the restricted reduced-form solution to the model. In this case, $B = [0 \ b_2]$ 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, with the survey expectation of inflation for period $t+1$ made in period $t$ denoted $\pi_{t+1,t}^s$.

$$\pi_t = \pi_{t+1,t}^s + \gamma y_t$$

$$y_t = \alpha y_{t-1} + \epsilon_t$$

(1.4)

In this case, how to solve the model is less clear. On the one hand, because the survey expectation is observable, one need not “solve out” the expectations in equation (1.4) 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 (1.4). Should one wish to simulate the model forward in time from arbitrary initial conditions, or examine its behavior under alternative policy assumptions, one would need to specify how the survey expectation 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:

$$\pi_t = \pi_{t+1,t}^s + \gamma y_t + \epsilon_t$$

$$\pi_{t+1,t}^s = \pi_{t+2,t}^s + \gamma y_{t+1,t}^s$$

(1.5)

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 by now be obvious that the iteration continues, and one cannot use the output process in (1.4) to quickly solve for all future output expectations (if one did, then we’d be back 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 remains.

So one needs a strategy for modeling survey expectations in a general equilibrium setting such as those in fully-articulated DSGE models, or even simple models such as the toy model described above. In the modeling exercise below, we will employ 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 below, and will ultimately be guided by empirical considerations as well as theoretical purity.

2. **Reduced-form and partial equilibrium evidence on the usefulness of surveys**
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 it), but to demonstrate the strong correlations between survey variables and key macro variables in regression equations that evoke standard macroeconomic relationships.

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 structural shocks with significant time series structure; and that the key slope parameters are reasonably well-identified, although the next section will pursue that issue more rigorously.

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.

**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 toy model in equation (1.1) above:

\[
\pi_t = \pi^S_{t+1, t} - b(U_t - U_t^*) + w^d \pi_t^e + w^f dp_t^f
\]  
(2.1)

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.\(^4\) Inflation is measured as 400 times the log change in the total CPI, as 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 estimation, as the survey expectations are recorded in the middle of quarter \( t \) and thus can only contain price and output information for quarter \( t-1 \) and earlier.\(^5\) Both the unemployment

\(^4\) 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.

\(^5\) Replicating these equations using the one quarter lag of expectations variables again preserves the conclusions presented in the paper in all essential respects.
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.\(^6\) Restricting inflation expectations to enter with a coefficient of one takes 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. Regression results and summary statistics are reported in panel 1.1 of Table 1 below. Fitted values are displayed in Figure 1. 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 empirical 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 (Gali 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 equation’s residuals (for the equation that excludes lagged inflation), 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 the next section will discuss modeling expectations in more detail, for illustrative purposes, we take a tentative step toward modeling survey expectations as suggested in the preceding section. We begin by iterating forward equation (2.1) and invoking the law of iterated expectations\(^7\):

\[
\pi^S_{t+1} = b_1 \pi^S_{t+2} - b_2 (U^S_{t+1} - U^S_{t+1}).
\] (2.2)

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\(^6\) 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, they are updated only in January of each year from 1991 to 2009. Thus no real-time data are available prior to 1991, and the yearly updates create some discontinuities in the series that are not desirable. 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.

\(^7\) More detail on deriving this equation is provided in section 3 below.
Of course, using the iterated forward version of equation (2.1) implies some conformity between the expectations process and the structure of the model. How well such a formulation captures the behavior of the survey expectations will be discussed in more detail in the system estimates in section 3 below.

The logic of equation (2.2) 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 (2.2) by making the SPF one-year expectations dependent on the longer-run inflation expectations, $\Pi_{t+1}^s$, and on the SPF forecast of the unemployment rate one quarter forward, $U_{t+1}^s$, less the natural rate in the next period, $U^*_t$ (we use the CBO’s estimate of the natural rate one period ahead).

$$ \pi_{t+1}^s = b_1 \Pi_{t+1}^s - b_2 (U_{t+1}^s - U^*_t) .$$  \hspace{1cm} (2.3)

The single-equation results from estimating (2.3) 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.

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, driven by a real variable that 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—and we will assume below—that the long-run 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.

“$I-S$” curve (unemployment)

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

\[
U_t - U_t^* = u^e (U_{t+1,t}^* - U_{t+1}^*) + u^e (\rho_{t-1} - \bar{\rho}).
\]

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 the identification of the real rate term in the IS curve is often problematic (see Fuhrer and Rudebusch (2004)). In this section, we examine reduced-form relationships that include either a short-term or a longer-term real rate.

Panel 1.3 of Table 1 displays the results. 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.\(^8\)

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 is much diminished from 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 of no influence of the lagged dependent variable.

Because we lack data on long-term unemployment expectations, closing the expectations side of this equation is a bit more complicated than it is for the Phillips curve. We defer discussion of this aspect until the next section.

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\(^8\)For many models, a one percentage point change in the federal funds rate is roughly equivalent to a one-quarter to one-third 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.
Policy rule

While the general form of the policy rule follows that of 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 values; and (2) the long-run value for the 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

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

$$\tilde{i}_t \equiv i_t - (\Pi_{t+1}^u + \bar{\rho})$$

(2.5)

The results from OLS estimation of equation (2.5) are shown in panel 1.4 of Table 1. All 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.

Addressing potential simultaneity: single-equation results

In the Phillips and I-S regressions above, the presence of contemporaneous unemployment gap and real interest rate terms raises the possibility that these OLS regressions are contaminated by classical simultaneous equations bias. In addition, although the survey expectations are collected in

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

10 A number of authors have explored possible explanations for the presence of interest-rate smoothing. One hypothesis is that in rules in which 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, a crude way of filtering the signal in noisy data on the central bank’s goals. The results in this paper, which make explicit use of forecasts of inflation and output that presumably filter the high-frequency noise in inflation and output but still find a role for the lagged policy rate, suggest that this is not a compelling explanation for interest rate smoothing.
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. While the systems approach in section 3 will address this issue more fully, we present instrumental variables estimates that partly alleviate the concern.

Simple instrumental variables regressions (GMM) are estimated for these two key equations. 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 are included in the instrument set. 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 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.\(^{11}\)

**Cointegration**

One simple explanation for the high correlation between expectations and realizations is that the two series are integrated of order one, and these regressions are simply uncovering a natural cointegration between forecast and forecasted variable. In this case, the exact timing of the regression would not matter much, and we would be less uncovering an interesting dynamic macro link and more uncovering the general tendency for these pairs of such series to move together at the zero frequency.

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\(^{11}\) As is often the case with GMM, these results vary more than one would like with changes in the details of the methodology. Iterated GMM results differ from non-iterated. 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.
However, conventional unit root tests suggest it is extremely unlikely that the correlation between forecasts and forecasted series arises from a common unit root over the sample in question (1982 to the present). Thus this explanation is ruled out.\textsuperscript{12}

Enhanced identification

The results 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 results from an exercise that is designed to highlight this advantage. The figure shows the estimated coefficient on the unemployment gap from rolling regressions of the Phillips curve in equation (2.1), 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). Cases one and three are estimated via OLS, and case three employs a standard GMM estimator. All 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 develops intermediate results. The figure highlights the advantage afforded by survey expectations in identifying this key structural parameter.

Together, these simple single-equation results suggest a strong empirical linkage between the survey expectations and the key macro variables in a DSGE model, through a variety of channels. The inclusion of these variables helps identify the key slope parameters in these equations, and greatly reduces 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 for

\textsuperscript{12} 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% 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.
all of these structural parameters on an equation-by-equation basis using OLS. The next section addresses this concern in more detail.

Equation Section (Next)

3. **A structural DSGE model with ubiquitous survey expectations**

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

   But these regressions cannot claim to provide true structural identification, for two reasons. First, apart from the timing of the expectations variables, the equations include some contemporaneous variables which may well be subject to simultaneity bias. Put 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 “I-S” 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 hope 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 without the convenience of being able to solve 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 theory-model in which they are embedded. However, due to inherent limitations in available data, it will be impossible to be completely consistent across all facets of the model. For example, the long-run (10-year average) expectations that are available for inflation, and that loosely speaking did the iterating
forward for us in the Phillips curve, are not available for unemployment, where they might in principle perform a similar function in the forward-looking I-S equation.

To anticipate some of the results in this section, we will find that it is relatively straightforward from an empirical perspective 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 difficult. As a consequence, we will make some compromises in closing the expectations components of the model. These compromises are largely unavoidable given the departure from rational expectations and given data limitations. In section 4, which evaluates the empirical performance of the model, we will argue that these compromises are justified by greater empirical success in a number of key dimensions.

Price-setting:

The model for price-setting follows closely the strategy in section 2. 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. We take this approach in part for simplicity, and in part because many of the additions to simpler models were made in response to observed deficiencies of the simpler 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

$$\pi_t = \beta \pi_{t+1} + \lambda mc$$

(3.1)

For a reasonable set of assumptions, one can show that marginal cost will be proportional to either the output or the unemployment “gap,” so that we can equivalently write equation (3.1) as

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

(3.2)

where $\pi^u$ is a function of the standard Calvo parameters underlying $\lambda$, 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 identification of key macro parameters, we allow

---

13 See Blanchard and Galí (2010) for a derivation of a NKPC with unemployment.
for the independent effects of food and energy prices on the CPI as “supply shifters,” thus augmenting the simple Phillips curve as follows

\[ \pi_t = \beta \pi^S_{t+1} - \pi^u(U_t - U^*_t) + w^e \Delta p_t^e + w^l \Delta p_t^f. \]  

(3.3)

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

Note that 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 one to use the average expectation as a sufficient statistic for all the individual expectations, 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 \( S_t x^S_{t+i,t+1} = x^S_{t+i,t} \)—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 (3.2) forward one period, and ignoring for the moment the effect of food and energy prices, we obtain

\[ \pi_{t+1} = \beta \pi^S_{t+2,t+1} - \pi^u(U_{t+1} - U^*_{t+1}). \]

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

\[ \bar{\pi}_{t+1} = \beta \bar{\pi}^S_{t+2,t+1} - \pi^u(U_{t+1} - U^*_{t+1}). \]  

(3.4)

Of course, this iteration could in principle be carried forward into the infinite future. But in practice, we do not have survey expectations into the infinite future. Thus we proceed as in section 2 and capture the spirit of this iteration, which would make one-period-ahead expectations a function of an extended sequence of short-term unemployment gap expectations. We approximate the long sequence of expected unemployment gaps with the SPF measure of the 10-year average expected inflation rate, as this measure should embody—according to the underlying logic of the model—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

---

14 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

\[ \pi_{t+1} = A \pi_t^s - \pi^* (U_{t+1}^s - U_t^s) \]  

(3.5)

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 when we discuss the I-S curve below.

Energy and food prices, which enter equation (3.3), are assumed to follow simple AR processes in log changes:

\[ dp_t^e = a^e dp_{t-1}^e \]  

(3.6)

\[ dp_t^f = a^f dp_{t-1}^f \]  

(3.7)

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 \( \pi^* \). The inflation goal can deviate from its long-run with some persistence, which we model via a partial adjustment equation with parameter \( \gamma \)

\[ \Pi_{t, t}^s = \gamma \Pi_{t-1, t}^s + (1 - \gamma) \pi^* \]  

(3.8)

OLS estimates of equation (3.8) imply a value of \( \lambda \) of 0.95, and that value is used throughout the remainder of the paper.

**IS curve**

Underlying the “I-S” 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

\[ c_t = \beta E_t c_{t+1} - \sigma (\rho_t - \bar{\rho}) \]  

(3.9)

where \( \rho_t \) and \( \bar{\rho} \) are a real rate of interest and the long-run equilibrium value of that rate, respectively. We will take the tack of many simple models in the literature and assume that capital investment is either absent or proportional to consumption, and government spending is fixed, so that equation (3.9) may equivalently be written as an output equation, 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 section 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, and one can thus substitute the unemployment gap for the output gap to arrive at an unemployment-based I-S curve:\(^{15}\):

\[
U_t - U_t^* = u^{ae}(E_t U_{t+1} - U_t^*) + u^o(\rho_t - \bar{\rho})
\]  

(3.10)

The real rate here is defined as the difference between the one-year short 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:

\[
U_t - U_t^* = u^{ae}(U_{t+1}^S - U_t^*) + u^o(\rho_t - \bar{\rho})
\]  

(3.11)

As with the price equation, this equation is complete given observations on the survey expectations for unemployment one period ahead, 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 (3.11) forward one period:

\[
U_{t+1} - U_{t+1}^* = u^{ae}(U_{t+2}^S - U_{t+1}^*) + u^o(\rho_{t+1} - \bar{\rho})
\]

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 \(t\):

\[
U_{t+1,t}^S - U_{t+1}^* = u^{ae}(U_{t+2,t}^S - U_{t+1}^*) + u^o(\rho_{t+1} - \bar{\rho})
\]  

(3.12)

The logic of this equation parallels that of the NKPC: The expected unemployment gap should be thought of as the average of a sequence of expected real interest rates. Thus we could in principle link the one-period-ahead inflation expectation to a long-term (e.g. ten-year average) unemployment expectation, which would implicitly capture a sequence of short-run expectations of future real interest rates. But the SPF does not collect such a variable on a consistent basis over a long sample,\(^{15}\)

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\(^{15}\) We could leave the I-S curve in terms of an output gap, although 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. The unemployment rate concept has remained relatively stable. 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.
so we pursue a somewhat different strategy. In a manner similar to the method employed for the price sector, we tie the unemployment expectation to a one-year-ahead expectation—the longest horizon collected in the SPF dataset over the sample since 1982

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

(3.13)

As with the price-setting solution, we would normally impose that the longer-term expectation for the unemployment gap is tied down to the model’s steady-state.

Whereas the price sector implies immediate response of short-run expectations to movements in the long-run inflation expectation (the central bank’s inflation goal), equation (3.5), short-run unemployment expectations appear to adjust more sluggishly. More precisely, initial estimates of equation (3.13) show persistent deviations of the one-quarter expectation from the fundamentals specified in the equation. Figure 4 shows the difference between one-quarter and one-year-ahead unemployment expectations in the SPF. As the figure indicates, the gaps persist for quite a few years, also suggesting a slow adjustment. An error-correction equation linking changes in the short-run expectations to the long-run expectations finds error-correction of about 0.25 per quarter (and no error-correction of the long-run towards the short-run expectation).

Thus we allow for partial adjustment towards the longer-run expectations implied by equation (3.13). Equation (3.14) allows for data-determined partial adjustment of the short-run unemployment expectation to the longer-run expectations

$$U_{t+1}^S - U_{t+1}^* = \mu [u^w (U_{Y,t}^S - U_{Y,t}^*) + u^r (\rho_{t} - \bar{\rho})] + (1 - \mu)(U_{t+1}^S - U_t^*),$$

(3.14)

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.

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16 An interesting but recent exception is the set of official projections of the Federal Open Market Committee participants, which include projections for the long-run value of inflation, unemployment, real GDP growth and the federal funds rate.

17 The estimated equation is

$$\Delta U_{t+1,1}^S = -0.25 \ (U_{t+1,1}^S - U_{t+1,1}^*) + 0.49 \ \sum_{i=1}^{2} \Delta U_{t+1,i}^S + 0.14 \ \sum_{j=1}^{2} \Delta U_{t+1,j}^S + 0.019 \ \text{ (0.0058)} \ (0.00030) \ (0.26) \ (0.43)$$

Where $p$-values are displayed in parentheses under the coefficient estimates, and the sum of the coefficients and their $p$-value is displayed in front of the summation terms.

18 Initial attempts at estimation without allowing 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.
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.\textsuperscript{19} We will examine the importance of this partial adjustment mechanism, specifically by testing the ability of the data to distinguish between the influence of lagged expected versus lagged realized unemployment in section 4.

In the absence of a measure of the long-term expectation—and because the steady state for the gap should be zero in this simple model—we close the model by linking the one-year survey expectation to the model’s rational expectation of unemployment over the next four quarters

\[ U_{yt}^s = 0.25E_t(U_{t+1} + U_{t+2} + U_{t+3} + U_{t+4}) \]  

(3.15)

This guarantees that the survey expectations will converge to the appropriate steady state for the unemployment gap (zero) in the long run.

**Interest rates**

In many models, the appropriate real rate of interest for the I-S 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 (by iterating forward the Euler equation into the infinite future. The standard definition of the short-term real interest rate is just the difference between the current short-term policy rate and the one-period-ahead expected inflation rate \( \rho_t \) is just the difference between the current short-term policy rate and the one-period-ahead expected inflation rate

\[ \rho_t \equiv i_t - \pi_{t+1}^s \]  

(3.16)

As in many studies, we find that identification of the IS curve is not straightforward. As in the reduced-form section above, 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—estimated coefficients are often of the wrong sign with quite large standard errors. As a practical compromise, we define the real rate as the difference between the one-year-ahead expected Treasury bill rate and the one-year-ahead expected inflation rate, or

\[ \rho_t \equiv i_{yt}^s - \pi_{yt}^s \]  

(3.17)

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

Next 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 funds rate, $\tilde{i}$, from its long-run equilibrium as

$$\tilde{i}_t \equiv i_t - (\Pi_{L_t}^S + \bar{\rho}) \tag{3.18}$$

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

$$\tilde{i}_t = a\tilde{i}_{t-1} + (1-a)[\tilde{i}^S_t (\pi^{S}_{t+1,t} - \Pi_{L_t}^S) - \tilde{i}^S_t (U^{S}_{t+1,t} - U^*_t)] \tag{3.19}$$

It remains to close the model with an equation for the one-year-ahead SPF forecast for the 3-month Treasury bill, $i^{S}_{Y,t}$. We assume that the forecasts implied by the policy rule for the funds rate will provide a reasonable approximation to the SPF’s forecasts of the Treasury bill over the next year. Thus the model’s forecast over the average short rate over the next four quarters is the rational expectation implied by the policy rule (and the rest of the model)

$$i^{S}_{Y,t} = 0.25E_t(i_{t+1} + i_{t+2} + i_{t+3} + i_{t+4}) \tag{3.20}$$

Note that wherever rational expectations appear in the model, they of course take into account the role that survey expectations play in the short-run evolution of the key variables. This 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.

Equation Section (Next)

4. 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

²⁰ Standard convergence statistics suggest that both jointly and individually, all the simulated posterior distribution estimates have fully converged.
information about the prior distributions assumed for each of the parameters. Figure 5 plots the associated parameter distributions, along with prior distributions, for each of the parameters.

The system estimates generally do not differ too dramatically from the OLS estimates presented in Table 1. But some differences are worthy of note. The key elasticities in the Phillips and I-S curves, $\pi^u$ and $u^e$, 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. Still, the estimates imply reasonably aggressive responses to expected inflation and unemployment gaps. And 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 key equations in the model, 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 2. 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. 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 I-S curve 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, suggesting that the ability of the model to distinguish between the I-S 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, out-of-sample performance**

As estimated, the steady-state of the model 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

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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.

22 Note that for comparability with the OLS estimates, the inflation coefficient reported in Table 3 is the sum of $i^e$ 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 $A^{\pi}$ to one, so that the steady-state for the key variables is as expected, and as summarized in table 4b.23

The model 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 two 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, unemployment, and the policy rate during this exceptional period.

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

$$
\epsilon_i^t = \lambda y_{i-1}^t + \beta_i X_i^t + \epsilon_t
$$

(4.1)

where $\epsilon_i^t$ is the estimated structural disturbance for the inflation or unemployment gap equation, $y_{i-1}^t$ is the lagged value of one of these variables, and the term $\beta_i X_i^t$ represents the other variables that enter the equation. The coefficient of interest is $\lambda$, 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 I-S curves.

As the table indicates, consistent with the results in section 2, 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

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23 Note that this parameter restriction falls outside the 95th percentile of the simulated posterior distribution for $A^{\pi}$. A Wald test of this restriction rejects it convincingly.
unemployment expectations represented in equation (3.14). This entails modifying the Phillips curve and “I-S” equations as follows:

\[\pi_t = (1 - \pi^F)\pi_{t-1} + \pi^F \pi^F_{t+1} - \pi^u (U_t - U_t^*) + w^r dp^r_t + w^f dp^f_t\]

\[U_t - U_t^* = u^w (U^S_{t+1} - U^S_{t+1}) + (1 - u^w) (U_{t-1} - U_{t-1}) + u^d (\rho_t - \bar{\rho})\]

and estimating the parameters \((1 - \pi^F), (1 - u^w)\) to assess the importance of lagged dependent variables.

Note first that the presence of the partial-adjustment term in the expected unemployment equation (3.14) bears dramatic implications for the success of the model 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 “I-S” curve and for expected unemployment deteriorates terribly in the absence of error-correction.24

The posterior modes of the Bayesian estimates of \((1 - \pi^F), (1 - u^w)\) in equations (4.2) 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 0.84, with a standard error of 0.065. Figure 10 displays the economic significance of the estimated lagged unemployment coefficient \((1 - u^w)\) by simulating the model at the parameter values estimated in the top panel of Table 6 (the dashed black line) and setting \((1 - u^w)\) 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 no 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 I-S 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 success of the model 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

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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.
presence of inertia in expectations. Thus the model is able to distinguish clearly 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”

This paper has not performed a head-to-head comparison of rational expectations with survey expectations, although other papers have done so (see Del Negro and Eusepi 2010, Nunes 2010). A simple way to perform such a comparison is to augment the model equations (3.3) and (3.11) so that the expectations that enter each equation are a linear combination of rational and survey expectations, with weights \( \lambda \) and \((1-\lambda)\), as follows.

\[
\begin{align*}
\pi_t &= \lambda E_t \pi_{t+1}^s + (1-\lambda) \pi_{t+1}^r - \pi^\prime (U_t - U_t^s) + w^s dp_t^s + w^d dp_d^s \\
U_t - U_t^s &= \lambda E_t (U_{t+1} - U_{t+1}^s) + (1-\lambda) (U_{t+1}^s - U_{t+1}^r) + u^s (\rho_{t-1} - \bar{\rho})
\end{align*}
\]

Under the null hypothesis that \( \lambda=0 \), the rational expectations are unimportant in the determination of the key variables in the model. As \( \lambda \) goes to 1, only the rational expectations matter, and the survey expectations (and equations that determine their evolution) are irrelevant.

Estimating this model over the same sample period, we obtain a point estimate from a FIML estimator of 0.013, although the parameter is imprecisely estimated. The bottom panel of table 6 presents a set of hypothesis tests, both likelihood-ratio and Wald tests, that assess the relative importance of rational versus survey expectations in this model. As the table indicates, given the unconstrained estimate of \( \lambda =0.001 \), it is not surprising that one cannot reject the hypothesis that \( \lambda=0 \), but one can also handily reject the hypothesis that \( \lambda \) is any value greater than 0.1. These estimates suggest at best a small and insignificant role for rational expectations in this model, once the information in survey expectations is taken into account.

Reduced-form models of survey expectations and identification

Acknowledging the \textit{ad hoc} nature of some of the modeling assumptions in section 3, one might be drawn towards more reduced-form representations of survey expectations as a simple means of closing the model. This section explores that option.
Instead of employing semi-structural equations for the key expectational variables in the model, \( x^S_{t+1,t}, U^S_{t+1,t}, t^S_{y,t} \), we instead substitute simple VAR equations for these variables of the form indicated in equation (4.3)

\[
x^S_{t+1,t} = \sum_{j=1}^{3} B_j X_{t-j} + e_t,
\]

where \( x^S_{t+1,t} \) is a survey expectation measure for one of the key model variables, and \( X_{t-j} \) is a vector of the lagged values of these variables as well as all of the non-expectations variables in the structural model. 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 3 and 4: 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. Put differently, these results suggest that the survey expectations at least loosely conform to the structure of the model within which they have been embedded, and 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.

5. Conclusions

The development of DSGE models has made significant progress over the past twenty 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 DSGE model problems with identification, inclusion of lagged dependent variables that stands in conflict with evidence from micro data, and excessive reliance on highly correlated structural shocks.

The paper suggests that the improvements afforded by substituting “real expectations”—proxied by surveys of actual forecasts—are substantial. First, these expectations serve well as expectations proxies in the standard linearized first-order conditions that make up DSGE models. Second, they 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 micro data. No more lags in the Phillips curve and the IS curve! Third, they obviate 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 over-
optimistic to suggest that all identification issues are solved. Fifth, they strongly dominate the incorporation of rational expectations into such models in a head-to-head empirical test. Sixth, the tests in section four 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 \textit{ad hoc} reduced-form solutions to full rational expectations.

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

References


Data Appendix

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mnemonic</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inflation</td>
<td>( \pi_i )</td>
<td>400 times the log change in the total consumer price index</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>( U_t )</td>
<td>Civilian unemployment rate</td>
</tr>
<tr>
<td>Natural rate</td>
<td>( U^*_t )</td>
<td>NAIRU estimate, Congressional Budget Office</td>
</tr>
<tr>
<td>Energy price</td>
<td>( dp^e_t )</td>
<td>400 times the log change in the energy sub-index of the CPI</td>
</tr>
<tr>
<td>Food price</td>
<td>( dp^f_t )</td>
<td>400 times the log change in the food sub-index of the CPI</td>
</tr>
<tr>
<td>Federal funds rate</td>
<td>( i_t )</td>
<td>Quarterly average of monthly observations of the effective federal funds rate</td>
</tr>
<tr>
<td>10-year govt. yield</td>
<td>( R_t )</td>
<td>Quarterly average of monthly observations of the 10-year constant-maturity Treasury yield</td>
</tr>
</tbody>
</table>

Survey expectations, Survey of Professional Forecasts (SPF)

<table>
<thead>
<tr>
<th>Expectation</th>
<th>Formula</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>One-year inflation expectation</td>
<td>( \pi^S_{t+1,t} )</td>
<td>Average of the median inflation expectation over next four quarters from the SPF</td>
</tr>
<tr>
<td>Long-run inflation expectation</td>
<td>( \Pi^S_{L,t} )</td>
<td>Average of the median inflation expectation over next ten years from the SPF</td>
</tr>
<tr>
<td>One-quarter unemployment expectation</td>
<td>( U^S_{t+1,t} )</td>
<td>Median expectation of the civilian unemployment rate for the next quarter</td>
</tr>
<tr>
<td>One-year unemployment expectation</td>
<td>( U^S_{Y,t} )</td>
<td>Median expectation of the average civilian unemployment rate during the four quarters of the next calendar year</td>
</tr>
<tr>
<td>One-year Treasury-bill expectations</td>
<td>( i^S_{Y,t} )</td>
<td>Median expectation of the average 3-month Treasury bill rate over the next four quarters</td>
</tr>
</tbody>
</table>

Note: All SPF expectations taken from the Philadelphia Fed website (http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/)

Observations from 1990:Q3 to the present represent information through the middle of the second month of the quarter (middle of February, May, etc.). 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 in the paper takes this 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 suggest that it is “similar.”
### Table 1
Regression results, simple single-equation models

#### 1.1 Inflation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected inflation</td>
<td>1</td>
<td>(imposed)</td>
</tr>
<tr>
<td>Unemployment gap</td>
<td>-0.069</td>
<td>0.0036</td>
</tr>
<tr>
<td>Change in food prices</td>
<td>0.073</td>
<td>0.0044</td>
</tr>
<tr>
<td>Change in energy prices</td>
<td>0.11</td>
<td>0.00</td>
</tr>
</tbody>
</table>

*R²: 0.89*

#### 1.2 Inflation expectations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long-run inflation expectation</td>
<td>0.75</td>
<td>0.00</td>
</tr>
<tr>
<td>One-quarter-ahead unemployment expectation</td>
<td>-0.21</td>
<td>0.00</td>
</tr>
</tbody>
</table>

*R²: 0.89*

#### 1.3a Unemployment gap – long rate

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>One-quarter-ahead unemployment expectation</td>
<td>1.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Long-term real interest rate (R10-PTR)</td>
<td>0.028</td>
<td>0.01</td>
</tr>
</tbody>
</table>

*R²: 0.99*

#### 1.3a Unemployment gap – short rate

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>One-quarter-ahead unemployment expectation</td>
<td>1.04</td>
<td>0.00</td>
</tr>
<tr>
<td>Short-term real interest rate ( (i_{Yt}^s - \pi_{Yt}^s) )</td>
<td>0.022</td>
<td>0.036</td>
</tr>
</tbody>
</table>

*R²: 0.99*

#### 1.4 Policy rule (Funds rate deviation)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged funds rate</td>
<td>0.81</td>
<td>0.00</td>
</tr>
<tr>
<td>SPF 4-quarter inflation expec.</td>
<td>0.46</td>
<td>0.015</td>
</tr>
<tr>
<td>SPF 1-quarter unemployment expect.</td>
<td>-0.43</td>
<td>0.000</td>
</tr>
</tbody>
</table>

*R²: 0.93*

### Table 2
Importance of lagged dependent variables in key equations

<table>
<thead>
<tr>
<th>Equation</th>
<th>Sum of lagged coefficients</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phillips curve</td>
<td>0.0062</td>
<td>0.96</td>
</tr>
<tr>
<td>Unemployment gap (“IS”)</td>
<td>0.23</td>
<td>0.00</td>
</tr>
<tr>
<td>Specification</td>
<td>Survey Expectation</td>
<td>Rational Expectation (Ex_{t+1})</td>
</tr>
<tr>
<td>---------------</td>
<td>-------------------</td>
<td>---------------------------------</td>
</tr>
<tr>
<td>1.</td>
<td>1.17 (0.077)</td>
<td>-</td>
</tr>
<tr>
<td>2.</td>
<td>1.0 (imposed)</td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>0.81 (0.069)</td>
<td>0.19 (0.069)</td>
</tr>
<tr>
<td>4.</td>
<td>-</td>
<td>0.48 (0.12)</td>
</tr>
<tr>
<td>5.</td>
<td>-</td>
<td>1.0 (imposed)</td>
</tr>
</tbody>
</table>

**“I-S” curve – long-term real rate**

<table>
<thead>
<tr>
<th>Specification</th>
<th>Survey Expectation</th>
<th>Rational Expectation (Ex_{t+1})</th>
<th>Real interest rate</th>
<th>p-value, Hansen’s J</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>1.05 (0.010)</td>
<td>-</td>
<td>0.0076 (0.011)</td>
<td>0.19</td>
</tr>
<tr>
<td>2.</td>
<td>1.0 (imposed)</td>
<td>-</td>
<td>0.062 (0.010)</td>
<td>0.64</td>
</tr>
<tr>
<td>3.</td>
<td>1.10 (0.11)</td>
<td>-0.10 (0.11)</td>
<td>0.058 (0.010)</td>
<td>0.56</td>
</tr>
<tr>
<td>4.</td>
<td>-</td>
<td>1.07 (0.022)</td>
<td>0.056 (0.029)</td>
<td>0.92</td>
</tr>
<tr>
<td>5.</td>
<td>-</td>
<td>1.0 (imposed)</td>
<td>-0.0042 (0.014)</td>
<td>0.86</td>
</tr>
</tbody>
</table>

**“I-S” curve – short-term real rate**

<table>
<thead>
<tr>
<th>Specification</th>
<th>Survey Expectation</th>
<th>Rational Expectation (Ex_{t+1})</th>
<th>Real interest rate</th>
<th>p-value, Hansen’s J</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>1.06 (0.011)</td>
<td>-</td>
<td>-0.0088 (0.010)</td>
<td>0.38</td>
</tr>
<tr>
<td>2.</td>
<td>1.0 (imposed)</td>
<td>-</td>
<td>-0.068 (0.011)</td>
<td>0.86</td>
</tr>
<tr>
<td>3.</td>
<td>1.04 (.067)</td>
<td>-0.04 (.067)</td>
<td>-0.073 (0.015)</td>
<td>0.82</td>
</tr>
<tr>
<td>4.</td>
<td>1.06 (0.020)</td>
<td>-</td>
<td>0.038 (0.020)</td>
<td>0.89</td>
</tr>
<tr>
<td>5.</td>
<td>1.0 (imposed)</td>
<td>-</td>
<td>-0.0036 (0.012)</td>
<td>0.86</td>
</tr>
</tbody>
</table>

**Figure 1**

*Fit of OLS regressions for key macro variables*

- **Inflation**: Shows actual and fitted data over the years 1980 to 2020.
- **Inflation expectations**: Displays fitted data from 1980 to 2020.
- **Unemployment gap (IS)**: Graphs the unemployment gap from 1980 to 2020.
- **Policy rule (Funds rate - long-run value = PTR + 2)**: Illustrates the policy rule over years 1985 to 2010.

**Figure 2**

*Autocorrelations of equation shocks*

- **Phillips curve residual autocorrelations**
- **IS curve residual autocorrelations**

---

33
Comparison of identification in Phillips curve with alternative expectations proxies

Unemployment gap coefficient, Rolling regression estimates, window size = 60

*p coefficients constrained to 1

Figure 3

Comparison of identification in Phillips curve with alternative expectations proxies

Unemployment gap coefficient, Rolling regression estimates, window size = 60

*p coefficients constrained to 1

Coefficient estimates

- Survey model
- BL Phillips model
- RE model (GMM)

198301 198503 198801 199003 199301 199503 199801

p-values

198301 198503 198801 199003 199301 199503 199801
Table 4
Estimates from simulated posterior distribution
1 million replications

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Maximum</th>
<th>Median</th>
<th>Memo: OLS</th>
<th>Std. Dev.</th>
<th>5th percentile</th>
<th>95th percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi^e$</td>
<td>0.19</td>
<td>0.18</td>
<td>0.069</td>
<td>0.055</td>
<td>0.094</td>
<td>0.27</td>
</tr>
<tr>
<td>$A^e$</td>
<td>0.89</td>
<td>0.89</td>
<td>0.75</td>
<td>0.036</td>
<td>0.83</td>
<td>0.95</td>
</tr>
<tr>
<td>$u^{ue}$</td>
<td>0.99</td>
<td>0.98</td>
<td>1.03</td>
<td>0.025</td>
<td>0.94</td>
<td>1</td>
</tr>
<tr>
<td>$u^{ue}$</td>
<td>0.033</td>
<td>0.036</td>
<td>0.028</td>
<td>0.018</td>
<td>0.0091</td>
<td>0.069</td>
</tr>
<tr>
<td>$\bar{\rho}$</td>
<td>2.03</td>
<td>2.05</td>
<td>-</td>
<td>0.15</td>
<td>1.8</td>
<td>2.3</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.2</td>
<td>0.2</td>
<td>-</td>
<td>0.048</td>
<td>0.12</td>
<td>0.28</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.78</td>
<td>0.77</td>
<td>0.81</td>
<td>0.037</td>
<td>0.7</td>
<td>0.83</td>
</tr>
<tr>
<td>$i^{e}$</td>
<td>1.2</td>
<td>1.2</td>
<td>2.4</td>
<td>0.042</td>
<td>1.1</td>
<td>1.3</td>
</tr>
<tr>
<td>$i^e$</td>
<td>0.57</td>
<td>0.57</td>
<td>2.3</td>
<td>0.015</td>
<td>0.55</td>
<td>0.6</td>
</tr>
</tbody>
</table>

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>
<thead>
<tr>
<th>Parameter</th>
<th>Distribution</th>
<th>[Mean, variance, support]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi_u$</td>
<td>Gamma</td>
<td>[0.5, 0.2, 0.001, 1.2]</td>
</tr>
<tr>
<td>$A^{\pi}$</td>
<td>Beta</td>
<td>[0.7, 0.15, 0.001, 1]</td>
</tr>
<tr>
<td>$u^{\pi}$</td>
<td>Gamma</td>
<td>[0.9, 0.2, 0.2, 1.3]</td>
</tr>
<tr>
<td>$u^e$</td>
<td>Gamma</td>
<td>[0.2, 0.1, 0.001, 0.5]</td>
</tr>
<tr>
<td>$\bar{\rho}$</td>
<td>Gamma</td>
<td>[2.5, 0.8, 0.001, 6]</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Beta</td>
<td>[0.3, 0.1, 0.001, 0.99]</td>
</tr>
<tr>
<td>$a$</td>
<td>Beta</td>
<td>[0.7, 0.15, 0.2, 1.0]</td>
</tr>
<tr>
<td>$i^e$</td>
<td>Gamma</td>
<td>[1.0, 0.25, 0.001, 2.4]</td>
</tr>
<tr>
<td>$i^e$</td>
<td>Gamma</td>
<td>[1.0, 0.25, 0.001, 3.4]</td>
</tr>
</tbody>
</table>

| Shock variances | Uniform (non-informative) |

<table>
<thead>
<tr>
<th>Variable</th>
<th>Steady state</th>
<th>Value at estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi_t$</td>
<td>$\Pi_{L,t}^S$</td>
<td>2.0</td>
</tr>
<tr>
<td>$U_t - U_t^*$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$dp_t^c$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$dp_t^f$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$i_t$</td>
<td>$\bar{\rho} + \Pi_{L,t}^S$</td>
<td>4.03</td>
</tr>
<tr>
<td>$\pi_{t+1,t}^S$</td>
<td>$\Pi_{L,t}^S$</td>
<td>2.0</td>
</tr>
<tr>
<td>$\Pi_{L,t}^S$</td>
<td>$\pi^*$</td>
<td>2.0 (imposed)</td>
</tr>
<tr>
<td>$U_{t+1,t} - U_t^*$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$U_{t+1,t}^S - U_t^*$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$i_{YY,t}$</td>
<td>$\bar{\rho} + \Pi_{L,t}^S$</td>
<td>4.03</td>
</tr>
</tbody>
</table>
Figure 5
Simulated Posterior Parameter Distributions
(1 million replications)
Figure 6
Simulated values of key variables at various parameter estimates
1983-2007

Inflation

Unemp. gap

Funds rate

Year

Data  ols  fiml  Bayes
Figure 7

Autocorrelations of estimated structural disturbances

Lags
Table 5

Omitted variable tests for lagged variables in structural equations

<table>
<thead>
<tr>
<th>Equation</th>
<th>Lag coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phillips</td>
<td>0.041</td>
<td>0.41</td>
</tr>
<tr>
<td>IS</td>
<td>0.29</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Figure 9

Importance of partial adjustment in expected unemployment equation

In-sample fit

Unemployment

Expected unemployment

- Actual
- with partial adj.
- Fast partial adj. (1-\(\mu\)=0.1)
<table>
<thead>
<tr>
<th>Table 6</th>
<th>System Tests</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Test for importance of lagged variables</strong></td>
<td></td>
</tr>
<tr>
<td>Coefficient</td>
<td>Posterior maximum</td>
</tr>
<tr>
<td>$(1 - \pi^\rho)$</td>
<td>0.058</td>
</tr>
<tr>
<td>$(1 - \mu^{UE})$</td>
<td>0.37</td>
</tr>
<tr>
<td>$(1 - \mu)$</td>
<td>0.84</td>
</tr>
</tbody>
</table>

**Test values, nesting RE and survey expectations**

<table>
<thead>
<tr>
<th>$\rho$-value</th>
<th>LR test</th>
<th>Wald test</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>0.83</td>
<td>0.99</td>
</tr>
<tr>
<td>0.0</td>
<td>0.83</td>
<td>0.99</td>
</tr>
<tr>
<td>0.1</td>
<td>0.22</td>
<td>0.0</td>
</tr>
<tr>
<td>0.2</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>0.3</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>0.5</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>0.7</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Memo: Unconstrained FIML estimate of $\lambda$

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0001</td>
<td>0.13</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 7</th>
<th>Estimates from simulated posterior distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expectations modeled with VAR equations</td>
<td></td>
</tr>
<tr>
<td>1 million replications</td>
<td></td>
</tr>
</tbody>
</table>

**Posterior distribution summary statistics**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Maximum</th>
<th>Median</th>
<th>Memo: OLS</th>
<th>Std. Dev.</th>
<th>5th percentile</th>
<th>95th percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi^\rho$</td>
<td>0.38</td>
<td>0.58</td>
<td>0.069</td>
<td>0.34</td>
<td>0.061</td>
<td>1.1</td>
</tr>
<tr>
<td>$\mu^{UE}$</td>
<td>0.7</td>
<td>0.68</td>
<td>1.03</td>
<td>0.26</td>
<td>0.26</td>
<td>1.1</td>
</tr>
<tr>
<td>$\mu^\rho$</td>
<td>0.13</td>
<td>0.23</td>
<td>0.028</td>
<td>0.14</td>
<td>0.025</td>
<td>0.47</td>
</tr>
<tr>
<td>$\rho$</td>
<td>2.5</td>
<td>2.8</td>
<td>-</td>
<td>1.5</td>
<td>0.4</td>
<td>5.4</td>
</tr>
<tr>
<td>$\pi$</td>
<td>0.95</td>
<td>0.65</td>
<td>0.81</td>
<td>0.23</td>
<td>0.25</td>
<td>0.97</td>
</tr>
<tr>
<td>$i^\pi$</td>
<td>2.2</td>
<td>3.2</td>
<td>2.4</td>
<td>2.2</td>
<td>0.37</td>
<td>7.5</td>
</tr>
<tr>
<td>$i^\rho$</td>
<td>1.6</td>
<td>2.6</td>
<td>2.3</td>
<td>2.3</td>
<td>0.32</td>
<td>7.5</td>
</tr>
</tbody>
</table>

Four blocks, 250,000 replications each, first 25,000 dropped for burn-in.
Figure 10
Importance of lagged dep. variable in unemployment equation
In-sample fit

- Actual
- with lagged unemp.
- No lagged unemp. (1-u_E=0.01)
Figure 11

Posterior parameter distributions
1000000 replications