Nowcasting and the Taylor Rule*

William A. Branch

University of California, Irvine

May 7, 2013

Abstract

Actual federal funds rates in the U.S. have, at times, deviated from the recommendations of a simple Taylor rule. This paper proposes a "nowcasting" Taylor rule that preserves the form of the Taylor rule but encompasses realistic assumptions on information observable to policymakers. Because contemporaneous inflation rates and output gaps are not observable at the time policy is set, policymakers must form "nowcasts." The optimal nowcast will depend, in part, on forecast uncertainty whenever policymakers have asymmetric costs to over- and under-predicting inflation and output. Empirical evidence shows that actual policy rates are consistent with those recommended by a nowcasting Taylor rule.

JEL Classifications: G12; G14; D82; D83
Key Words: Nowcasting, asymmetric loss, forecast uncertainty, monetary policy.

1 Introduction

The **?** rule provides a benchmark guide to monetary policymakers: the federal funds rate should be adjusted in response to deviations of the contemporaneous inflation rate from its long-run target and the output gap (i.e. deviations of contemporaneous output, in percentage points, from potential output).[1] Research that estimates Taylor rules with historical data

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[1] **?** recommends the policy rate should be set to 1 plus 1.5 times the inflation rate plus 0.5 times the output gap.

finds coefficient estimates in line with the **?** rule.[2] However, the Taylor rule features a number of departures, including the "too long for too low" period of 2003-2005 (**?**). During this period, the Taylor rule prescribed that the federal funds rate should be increased in 2003, a full year before policymakers began tightening rates.

This paper explores the ability of the Taylor rule to empirically fit historical policy rates by focusing on the forecasting problem faced by monetary policymakers: policymakers often rely on "nowcasts" of the current state of the economy. A point of departure for this paper is the observation that policymakers' nowcasts may be affected by their subjective forecast uncertainty if they evaluate forecast errors asymmetrically.[3] Specifically, the optimal nowcast will include a precautionary term that depends on two factors: (1.) their aversion to the over or under prediction and (2.) their forecast uncertainty. If policymakers fear over predicting inflation, then they will adjust their forecast of inflation down by a factor that is increasing in forecast uncertainty. Forecast uncertainty may lead to caution when adjusting interest rates.

This paper utilizes a unique aspect of the Survey of Professional Forecasters to identify nowcasts of inflation and the output gap from the probability forecasts of respondents.[4] The SPF is a reasonable proxy for the nowcasts of the FOMC as professional forecasters have very similar backgrounds to staff economists at the Federal Reserve. A "nowcasting Taylor rule" replaces contemporaneous inflation and output gap with its nowcasting values. This paper demonstrates that nowcasting Taylor rules can account for historical data on federal funds rates. The results show that, in line with **?**, the best fitting Taylor rule is consistent with policymakers averse to over predicting inflation and the output gap.

2   Nowcasting and the Taylor Rule

The generalized version of the **?** rule is a simple policy rule that takes the form

$$i_t = \alpha_0 + \alpha_\pi \pi_t + \alpha_x x_t \tag{1}$$

where i_t is the (average) federal funds rate, π_t is a four-quarter average inflation rate, and x_t is the output gap. The original Taylor rule set $\alpha_0 = r^* - 0.5\pi^*$, where $r^* = 2$ is the real interest rate and $\pi^* = 2$ is the central bank's inflation target. Although providing a relatively good historical fit to actual policy rates, **?** criticized Federal Reserve policy during 2003-2005 for having kept interest rates "too low for too long." The source of Taylor's criticism is clearly seen in Figure 1, which plots the Taylor rule over the period 1987.3-2009.4.[5] Rudebusch

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[2]See **?** for an extensive review of this literature.

[3]A body of research finds evidence of asymmetric loss functions, e.g. **?**, **?**, **?**, and **?**, which implies that forecasts depend on forecast uncertainty.

[4]**?**, **?**, **?** also make use of this aspect of the SPF. An existing literature makes use of point forecasts but not uncertainty. See **?**,**?**, **?**.

[5]This figure was generated by measuring inflation as the four-quarter average rate from the personal consumption expenditure price index excluding food and energy, i.e. $\pi_t = (1/4)\sum_{j=0}^{3} \pi_{q,t-j}$, where $\pi_{q,t} = 400\ln(P_t/P_{t-1})$, and the output gap is the difference between real GDP and potential output as measured

estimates the equation with least squares over the period 1987:Q4 to 2004Q4 and found estimates of $\alpha_0 = 2.04, \alpha_\pi = 1.39, \alpha_x = 0.92$. The estimated rule still exhibits a "too low for too long" period.

This paper begins with the observation that in practice monetary policymakers do not observe the current state of the economy rendering it impossible to include contemporaneous inflation and output gap measures in the policy rule. In its place, central banks respond to nowcasts of inflation and the output gap (**?**). A nowcasting Taylor rule is

$$i_t = \alpha_0 + \alpha_\pi \hat{E}_t \pi_t + \alpha_x \hat{E}_t x_t \tag{2}$$

where $\hat{E}_t$ is the policymaker's forecast of current economic variables, i.e. the nowcast.

What form should these nowcasts take? This paper follows (**?**, **?**, **?** and **?**) who provide evidence that forecasters hold asymmetric loss functions that evaluate positive and negative forecast errors differently. In such instances, forecasts may be biased by including a precautionary term that depends on subjective uncertainty and that will minimize the likelihood of errors in the more costly direction. It can be shown that, under suitable conditions, optimal nowcasts are of the form,

$$\hat{E}_t \pi_t = E_t \pi_t + \phi_\pi \hat{\sigma}_{\pi,t}^2$$
$$\hat{E}_t x_t = E_t x_t + \phi_x \hat{\sigma}_{x_t}^2$$

where E_t is the conditional expectation, and $\hat{\sigma}^2$ is the subjective forecast uncertainty.[6] If policymaker's have a symmetric loss function, then $\phi_\pi = \phi_x = 0$. When $\phi_j < 0, j = x, \pi$, then the forecaster considers over predictions more costly and so will include a precautionary term $(\phi_j \hat{\sigma}_j^2)$ that biases the nowcast.

3   Identifying Nowcasts

The Survey of Professional Forecasters (SPF) asks forecasters, each quarter, to provide point forecasts for inflation and output growth, among other things, as well as to report the histogram of their forecasts for the current year's annual inflation and output growth rates. Following **?**, **?**, and **?** we construct estimates of the probability distribution of each individual forecaster in the SPF, and then average moments across forecasters to arrive at a measure of aggregate forecast uncertainty. One complication is that the nowcasting Taylor rule depends on the forecasted value for the current (annual) inflation rate while the SPF probability forecasts are for the current year's inflation rate. Thus, the first-quarter

probability forecasts are for inflation over the next 4 quarters, the second-quarter is over the next 3 quarters, and so on.

The identification of current SPF probability forecasts begins with an observation: forecasters construct forecasts by projecting their model – whether, statistical or subjective – out-of-sample. Given a model and observed data, forecasters can construct a probability distribution over outcomes for the current quarter and all subsequent quarters, thereby, arriving at a probability distribution over possible inflation and output growth outcomes over the course of the year. The SPF asks forecasters to report the probability inflation and output growth will fall into one of 10 bins – such as, $[0\%, 1\%)$, $[1\%, 2\%)$... – and so forecasters report a distribution over these discrete outcomes. In order to identify the current quarter distribution, we must make an assumption about the way in which forecasters project their subjective distribution over the forecasting horizon. While the Appendix provides explicit details on the computations, we can summarize the identification assumption as follows: inflation and output growth are perceived to follow a random walk over the forecast horizon. This is a reasonable identifying assumption that is made because of data limitations and can be interpreted as forecasters perceiving that inflation and output growth follow a Markov chain with time and spatially invariant transition probabilities over the forecasting horizon.[7]

For each individual histogram, the subjective forecast distribution is estimated non-parametrically by a smooth kernel density estimator and parametrically via a generalized beta distribution (see ?).[8] Aggregate forecast uncertainty, in each quarter, is measured as the median interquartile range (IQR), or standard deviation, across individuals. In addition to a measure of forecast uncertainty, the estimated full distributions can also be used to compute $E_t \pi_t$, the conditional forecast for inflation. Below, we use the Greenbook estimate for conditional forecasts of the output gap.

The SPF probability forecasts, over this sample, ask forecasters for their forecast of real GDP growth. To construct a measure of output gap uncertainty, using real GDP growth uncertainty, requires the identifying assumption that all forecast uncertainty comes at the business cycle frequency and not in forecasts of potential GDP. This is a strong identifying assumption, but one that is necessary because of data limitations.[9]

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[7]There are two natural alternatives to this identifying assumption. First, assume that the forecasters perceive the bin outcomes as being drawn from a more generally defined Markov chain, where the transition probabilities come from the forecasters subjective distribution. Because these transition probabilities vary as forecasters in the SPF update their forecasting model over time, there are not sufficient degrees of freedom to identify all of the transition probabilities unless the draws are independent over the forecast horizon. Second, one could assume that survey respondents actually report their quarterly forecasts. The main qualitative results of the paper are robust to this alternative identifying assumption.

[8]Mathematica programs available from the author a wide range of robustness exercises for estimating Taylor rules, nowcasting Taylor rules, and inertial Taylor rules. The beta distribution imposes a single peak to the subjective distribution that however makes estimates of the moments from the distribution more reliable. ? estimate the distributions assuming a normal distribution, however the beta distribution is better able to capture the shifting skewness of the distributions that are a key element of the nowcasting story.

[9]The SPF asks forecasters for their estimate of potential GDP but not uncertainty in the growth rate of potential GDP. There has been influential research (e.g. ?) that suggests that uncertainty, and forecast errors, of potential GDP and the output gap plays a large role in the policymaking process. For the improved fit in this paper, especially over the 2003-2005 period, it is shifting inflation uncertainty that is the critical

Figure 2 plots the main estimated time series for uncertainty in the SPF. The left panel plots inflation uncertainty and the right panel plots real GDP growth uncertainty. Uncertainty tends to be cyclical. Importantly, uncertainty in both inflation and GDP growth elevate following the 2001 recession and, in particular, during the years 2003-2004. GDP growth uncertainty falls abruptly between 2002-2004, while inflation uncertainty recedes somewhat but remains elevated throughout the period. While Figure 2 plots the median forecast uncertainty, Figure 3 plot the full distribution of estimated uncertainty in the SPF. Clearly, in addition to the well-known dispersion in point forecasts in the SPF, there is considerable dispersion in forecast uncertainty as well.

Figure 4 plots the median skew of the individual histograms estimated with the beta distribution, which gives information about the evolving nature of uncertainty. One particular feature of Figure 4 warrants attention. Over the period 2002-2005 inflation probability forecasts are skewed towards low inflation. This is a key insight of the paper: the combination of relatively high forecast uncertainty (Figure 2) that is skewed towards low inflation rates (Figure 4) can provide a partial justification for the low federal funds rate during the period 2003-2005. One can also compare the skew in these estimated distributions with the policy statements released by the Federal Reserve to provide narrative support that the forecast uncertainty in the SPF is consistent with the FOMC's views about the state of the economy and forecasts.

Finally, the individual histograms can also be used to estimate ϕ_π, ϕ_x for each individual forecaster, following **?**.[10] We find estimated values for ϕ_π that range from -2.8 to 1.8 with a median value of 0.14. While for ϕ_x the estimated values range from -2.4 to -0.44 with a median value of $-.92$. **?** find similar values, and heterogeneity, in estimated ϕ_π, though they use actual realized values for inflation in place of the conditional forecasts used in the estimation here. Of course, because of the heterogeneity in estimated values of ϕ_π, ϕ_x there is no *a priori* reason to expect that policy nowcasts will align exactly with the median SPF nowcasts.

3.1   Further Discussion

That forecasters report probabilities attached to bins implies some subtle empirical issues. Since the survey respondent's probability is attached to a bin, rather than a number, some assumption needs to be made on how the reported probability is distributed across the bin. For the purposes of this paper, the analysis that follows assumes that when a forecaster reports a given probability attached to a bin they place that probability on the lower endpoint value of the bin.[11] For example, a 10% probability that inflation will lie between 1

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factor.

[10]After having constructed measures of $E_t x_{jt}, \hat{\sigma}^2_{j,t}$ for each forecaster i, it is straightforward to construct an estimate of ϕ_j as $\phi_{i,j} = -\frac{2}{T} \sum_{t=1}^{T} -e_{i,t}/\hat{\sigma}^2_{i,j,t}$ where $e_{i,t} = \hat{E}_t x_{j,t} - E_t x_{j,t}$, and $\hat{E} x_{j,t}$ is the point SPF forecast for forecaster i.

[11]The "bounds" approach (see **?**, **?**) places upper and lower bounds on the measures of central tendency by assuming that all weight is placed on either the lower or upper endpoint of the bins. Although this paper, does not directly interpret the estimated measures as a "lower bound", we impose that all weight is placed

and 2% are treated as a 10% probability that inflation will be 1%. In our view, this is a reasonable assumption as the survey forms filled out by respondents have the lower bound as a focal point. As an alternative, **?** assign the probability to the midpoints when calculating conditional forecasts. This alternative has no impact on the IQR and standard deviation uncertainty measures, though, it could impact the conditional forecasts. The effect of placing the probability mass at different points in an interval is a rightward shift of the estimated subjective distributions. Thus, we find that the main qualitative results of this paper are robust to either alternative, with a small quantitative impact on the estimated asymmetry coefficients. The measures of central tendency, though, will be overstating the dispersion in subjective distributions if forecasters do not assign probabilities to each bin in this uniform manner. For example, it is possible that a forecaster reporting a 10% probability in the $[1, 2)\%$ bin and 90% in the $[2, 3)\%$ bin is assigning 10% probability to 1.99% and 90% probability to 2.01 percent. In this case, assigning the probability mass to the lower endpoint of the bin clearly overestimates the subjective uncertainty. Conversely, it is possible that uncertainty is understated if forecasters assign probabilities to the furthest end points in two adjoining bins. Again, a forecaster reporting a 10% probability in the $[1, 2)\%$ bin and 90% in the $[2, 3)\%$ bin could actually be assigning 10% to 1.01% and 90% probability to 2.99 percent. The approach taken in this paper is a reasonable compromise, though it would be straightforward to extend the analysis to place upper and lower bounds on the measures of uncertainty.

The sample period is 1993:Q1-2008:Q3 (when data is available) where forecasters are asked for their probability forecasts of real GDP and the bin specifications are consistent. We end the sample before the federal funds rate hits the zero lower bound in 2008:Q4. We also checked that results are robust to cutting the sample in 2006:Q4 before the onset of the financial crisis and Great Recession. One other potential issue is that this is an unbalanced panel of forecasters. Forecasters often drop out of the survey permanently or reappear at later survey dates. Because the composition of forecasters in the survey changes, the median measures of uncertainty might not provide the best estimate of overall forecast uncertainty. In computing median point forecasts, **?** warn against analyzing median forecasts when the panel's composition changes and focus on subsamples with a fixed set of forecasters. This paper abstracts from these issues and leave the robustness of the results to a panel with a fixed composition to future research.

4   Empirical Results

This section considers the empirical performance of several variants of the nowcasting Taylor rule

$$i_t = \alpha_0 + \alpha_\pi E_t \pi_t + \alpha_x E_t x_t + \alpha_{\sigma_\pi} \hat{\sigma}_{\pi,t}^2 + \alpha_{\sigma_x} \hat{\sigma}_{x,t}^2 + \varepsilon_t \tag{3}$$

where $\hat{\sigma}_{j,t}^2, j = \pi, x$ are the median estimated standard deviations, or IQR's, from the SPF. $E_t \pi_t$ is measured as the median of the forecasts computed from the estimated histograms for

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on a particular point in the bin and consider robustness to whether the point is at the lower endpoint or the midpoint.

π_t (baseline) and from the Greenbook forecasts. $E_t x_t$ comes from the Greenbook forecast of the output gap.[12] In addition to estimates from the regression equation (3), we also report estimates of (2) where the nowcasts are computed as the median nowcasts from the SPF, i.e. $\hat{E}_t \pi = E_t \pi + 0.14 \hat{\sigma}_{\pi,t}^2$ and $\hat{E}_t x_t = E_t x_t - .92 \hat{\sigma}_{x,t}^2$.

Equation (3) is a more general specification of the nowcasting Taylor rule (2). This specification allows for separate policy responses to forecasts and uncertainty about the forecast. There are two equivalent interpretations to (3). First, when policy is set according to the nowcasting Taylor rule (2) then it is possible to recover the asymmetry parameter from the identities $\alpha_{\phi_\pi} = \alpha_\pi \phi_\pi$ and $\alpha_{\phi_x} = \alpha_x \phi_x$. Second, policy responds systematically to forecast uncertainty as a separate variable.[13] These two interpretations are equivalent as they both indicate that policy responds to forecast uncertainty by moving policy rates in a particular direction.

As a baseline, Table 1 reports least-squares regression results for estimated Taylor rules (i.e. without forecast uncertainty). For the Taylor rule (1) three different specifications are estimated. The first is a Taylor rule estimated with revised data, the second uses real-time data from the Philadelphia Federal Reserve's real-time database, while the third uses Greenbook forecasts. The coefficients are estimated over the sample 1993-2008:Q3, except for the specification that uses Greenbook forecasts where data is available through 2006. The baseline Taylor rule exhibits much stronger reaction coefficients to inflation and output gap than the Taylor (1993) rule and does not provide a very good fit to the historical data with an adjusted R^2 of 0.44. Using real-time data or Greenbook forecasts substantially improves the fit but with lower estimated values for α_π and higher estimated values for α_x than recommended by Taylor's rule.

Table 2 presents estimates for two variants of the nowcasting Taylor rule. The left hand column presents estimates for (2) using the median nowcasts from the SPF (i.e. with $\phi_\pi = 0.14$ and $\phi_x = -0.92$). The right column presents estimates of (3). Table 2 reports least-squares regression results for the sample 1993-2008:3, with Newey-West standard errors in parentheses.[14]

Across both specifications, the coefficient on the output gap is roughly similar but both estimates are higher than in the ? rule. For the interest rate rule that responds to the SPF

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[12]The forecast for the output gap comes from the Greenbook's estimated output gap at the time of the meeting in that quarter. This data is available through 2006. For analysis following 2006 we use the real-time output gap measured as the difference between the second release of real GDP (from the FRB Philadelphia) and the CBO's real-time estimate of potential output made during director's testimony for that year, as recorded by the ALFRED database at the Federal Reserve Bank of St. Louis. For robustness exercises, we estimated (3) with and without real-time data, with median point forecasts from the SPF, Greenbook forecasts of the output gap (when data available), and alternative measures of uncertainty. The importance of real-time data in estimated monetary policy rules has been emphasized by ?.

[13]A third alternative for non-zero estimates of $\alpha_{\phi_j}, j = \pi, x$ is that the policy rule equation (3) is misspecified. For example, the uncertainty variables could be correlated with some relevant omitted explanatory variable. This, of course, is an issue for all estimated Taylor rules. To address this possibility, the analysis below includes a large number of alternative specifications and robustness checks.

[14]Similar results are found when considering a sample period that ends in 2006 before the financial crisis and with Greenbook inflation forecasts.

nowcasts, the reaction coefficient to inflation is 2.34 a value that is above the 1.50 in the Taylor rule. This rule also fits the data better than the estimated Taylor rule in Table 1, but with an adjusted $R^2 = 0.51$ it does not fit as well as the Taylor rule estimated with real-time data or Greenbook forecasts.

The second specification does not impose that policymakers' nowcasts are the same as the median SPF nowcasts. Instead, the general form of (3) allows for a different response to uncertainty than the median asymmetry in the SPF. As mentioned above, the estimated asymmetry parameters exhibit considerable heterogeneity across forecasters and so there is no reason to expect that policymakers on the FOMC will have the same preferences as the median SPF forecaster. Estimates of (3) provide evidence on how the federal funds rate responds systematically to forecast uncertainty. The nowcasting rule (3) leads to a much improved fit to historical federal funds rate data. The second column provides estimates for the reaction coefficients in line with the estimated Taylor rules in Table 1. However, the estimates also show that the reaction to inflation forecast uncertainty is significantly different from zero. In particular, the response to inflation uncertainty is -0.99 and to output uncertainty it is -0.35.

There are two equivalent interpretations to the estimated results in column two of Table 2. First, when forecast uncertainty for inflation increases by 1% then the Federal Reserve will, all else equal, lower the federal funds rate by 99 basis points; conversely, when forecast uncertainty for output increases by 1% then the Federal Reserve decreases the federal funds rate by 35 basis points. These coefficients can be interpreted in light of Figures 2 and 4: inflation uncertainty is high precisely when probability forecasts for inflation are skewed towards low inflation outcomes. The correlation between the median uncertainty for inflation and the median skewness of the individual distributions is 0.64. Second, nowcasting implies estimated asymmetry parameters $\phi_\pi = -0.57$ and $\phi_x = -0.41$, values that fall into the range estimated for individual forecasters in the SPF. Recall $\phi_\pi < 0$ implies policymakers with a concern for over predicting inflation, and $\phi_x < 0$ reflects a precaution against over predicting the output gap.[15]

In part, the story for why the nowcasting rule (3) leads to an improved fit over the "too low for too long" period is that this was a period of high forecast uncertainty and federal reserve policymakers were particularly concerned with the possibility of low inflation. The median SPF forecaster, though, displays an aversion to under-predicting inflation. We can test whether the estimated asymmetry in the nowcasting rule is different from the SPF – and so, whether policymakers are responding just to private-sector nowcasts versus their own – by testing the null that $\alpha_{\sigma_\pi} = 0.14\alpha_\pi$ and $\alpha_{\sigma_x} = -0.92\alpha_x$. This produces a F-statistic of 16.61, thus rejecting the null. The best-fitting nowcasting Taylor rule has the central bank more concerned with over-predicting inflation, i.e. by being cautious against low inflation. This

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[15]This result is similar to a finding by **?** that interest rates react negatively whenever Greenbook forecasts of inflation are higher than the median SPF forecast. They interpret this finding as policymakers exercising caution because of forecast uncertainty or a concern about private-sector expectations becoming unanchored. Below, we consider a specification that also includes a reaction to private-sector forecasts that in a way that can distinguish between forecast uncertainty and a reaction to private-sector expectations. The results in this paper, then, are complementary to Coibion-Gorodnichenko.

result, in part, motivates an extension considered below that allows for a separate response to SPF expectations.

The exercise reported above uses actual federal funds rates to identify the extent that forecast uncertainty may matter in the decision making process. The explicit assumption is that the loss function of the FOMC may lead them to put weight on forecast uncertainty.[16] Alternatively, the private-sector may have nowcasts whose bias depends on forecast uncertainty and the central bank responds to private sector expectations, as in ?. ? provide evidence of asymmetric forecasts in the SPF, however, using these results and including private-sector expectations as a proxy for central bank nowcasts does not improve the empirical fit over the nowcasting rule.

Figure 6 compares the predicted interest rates from the estimated Taylor rule (Table 1, col. 2) and the estimated nowcasting rule (Table 2, col. 2) to the historical federal funds rate time series over the sample 1993-2008:3, while Figure 5 compares the estimated nowcasting Taylor rule to the ? rule. The nowcasting Taylor rule provides a substantially better fit to historical federal funds rates than the Taylor rules, especially over the 2003-2005 period. Incorporating nowcasting improves the fit relative to the estimated and original Taylor rules.

The improved fit over the 2003-2005 period is because, by lowering rates in response to the heightened uncertainty, policymakers act as if they expect inflation to be lower than their point estimate. Figure 7 plots the estimated nowcasts using the estimated asymmetry coefficients $\phi_\pi = -0.57$ and $\phi_x = -0.41$. The right panel plots inflation nowcasts and the left is for the output gap nowcasts. The solid line are the nowcasts and the dotted line are the conditional forecasts. For the output gap, nowcasts are close to the point estimates. For inflation, however, the nowcast is significantly lower than the conditional expectations predict. The right panel also plots Greenbook inflation forecasts (dotted line). Notice that Greenbook forecasts are especially similar to nowcasts over the 2003-2005 period.

5   Extensions

This section considers several extensions to the benchmark analysis: an inertial nowcasting rule, a rule that includes real GDP growth as an additional explanatory variable, a rule that responds separately to the difference between central bank and SPF forecasts, and a forward-looking rule that incorporates forecast uncertainty.

5.1   An Inertial Nowcasting Taylor Rule

Since generalized Taylor rules still exhibit substantial deviations from actual federal funds rates, a literature incorporates inertia into the Taylor rule via a partial-adjustment mecha-

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[16]An alternative explanation is provided by ? who computes optimal Taylor rule coefficients when the central bank is uncertain about the output gap.

nism. Following **?** and **?** an estimated inertial Nowcasting Taylor rule is

$$
\begin{aligned}
i_t &= (1-\rho)\hat{i}_t + \rho i_{t-1} + \varepsilon_t \\
\hat{i}_t &= \alpha_0 + \alpha_\pi E_t \pi_t + \alpha_x E_t x_t + \alpha_{\sigma_\pi} \hat{\sigma}^2_{\pi,t} + \alpha_{\sigma_x} \hat{\sigma}^2_{x,t}
\end{aligned}
$$

Table 3 provides coefficient estimates for the inertial nowcasting Taylor rule and an inertial Taylor rule with real-time data. Table 3 also presents estimates for an inertial rule where the smoothing is an AR(2) specification, following **?**. The inertial Taylor rule (left hand column) has an inflation response coefficient roughly in line with the non-inertial rule but the estimated value on the output gap is substantially higher. The inertial nowcasting Taylor rule (middle column) has estimated coefficient values that are slightly higher than in Table 2 and higher uncertainty response coefficients. The persistence coefficient ρ is significantly lower in the nowcast Taylor rule (0.67) than in the estimated Taylor rule (0.83). Both rules provide very good fits to historical data, as can be seen in Figure 8. An inertial nowcasting rule provides a close historical fit with an estimated degree of inertia that is lower than is typically reported. The systematic reaction to forecast uncertainty can account for a portion of the inertia, or gradual adjustment, exhibited in empirical Taylor rules. Similar results obtain for the AR(2) inertial rule which provides the best fit to historical federal funds rate, a finding in line with **?**.

5.2   A Nowcasting Rule with real GDP growth

? demonstrates the advantages of policy rules that respond to output growth rates (a "speed limit policy"). Recent empirical studies such as **?** find that policy rates adjust separately with real GDP growth and the output gap. One potential concern of identifying output gap uncertainty with output growth uncertainty is that the $\hat{\sigma}^2_x$ explanatory variable is proxying for an omitted variable such as real GDP growth. This section addresses these issues by formulating an extension of the nowcasting rule (3) that responds separately to real GDP growth. That is, we estimate the following rule:

$$
i_t = \alpha_0 + \alpha_\pi E_t \pi_t + \alpha_x E_t x_t + \alpha_{\sigma_\pi} \hat{\sigma}^2_{\pi,t} + \alpha_{\sigma_x} \hat{\sigma}^2_{x,t} + \alpha_g g_t + \varepsilon_t \tag{4}
$$

where g_t is the real GDP growth rate (using real-time data).

Table 4 reports coefficient estimates for the Taylor rule with real-time data and real GDP growth and the nowcasting Taylor rule with real GDP growth. For each rule, the reaction coefficients are in line with the values reported in (2) and the coefficients on real GDP growth are not significantly different from zero only for the real-time Taylor rule. The fit of the real-time Taylor rule is improved but the fit is not as good for the nowcasting Taylor rule. These results demonstrate that the improved fit of the nowcasting Taylor rule, and the role of uncertainty, are robust to this alternative specification.

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5.3 A Nowcasting Rule with Private-Sector Expectations

A considerable body of research demonstrates the economic benefits when policymakers systematically respond to private-sector expectations when setting policy rates. For example, ? show that a policy rule that responds to private-sector expectations (an "expectations-based rule") can implement optimal monetary policy even if private-agents do not have rational expectations. As another example, ? consider an estimated version of their policy rule that allows the central banks to respond to private sector expectations that differ from their own. Central banks may care about when private-sector expectations diverge from their own for a number of reasons such as: uncertainty about the central bank's forecasts, policy actions and communication when the central bank has superior information, and a concern about "falling behind the curve" if private-sector expectations become are self-fulfilling and become unanchored.

This section estimates the following nowcasting Taylor rule:

$$i_t = \alpha_0 + \alpha_\pi E_t \pi_t + \alpha_x E_t x_t + \alpha_{\sigma_\pi} \hat{\sigma}^2_{\pi,t} + \alpha_{\sigma_x} \hat{\sigma}^2_{x,t} + \alpha_{\triangle_\pi} \triangle_{\pi,t} + \alpha_{\triangle_x} \triangle_{x,t} + \varepsilon_t \qquad (5)$$

where $\triangle_{j,t}$ is the difference between the Greenbook and median SPF forecast for variable j. Here $E_t \pi_t$ are the Greenbook forecasts. This specification captures the aspect of ? that policymakers only respond separately to private-sector expectations when they differ from their own, but by controlling directly for the systematic response to forecast uncertainty (5) is better able to distinguish between uncertainty versus reacting to private-sector expectations.

Table 5 presents the results from estimating (5) with least-squares. There are a number of observations to be drawn from the estimates in Table 5. First, the coefficient estimates for $\alpha_\pi, \alpha_x, \alpha_{\sigma_\pi}, \alpha_{\sigma_x}$ have the same signs as, and are quantitatively similar to, the estimates presented in Table 2. The response coefficients to inflation and the output gap are, however, closer to values typically reported in the literature. The results in Table 5 show that the federal funds rate is consistent with a systematic response to differences between the central bank's inflation forecast and the private-sector, but the coefficient on differences in output growth forecasts is insignificant. Moreover, as in ? the central bank increases federal funds rates less aggressively when the private-sector's forecasts for inflation are below their own.

The fit of rule (5) is slightly higher than the baseline nowcasting rule. What accounts for the improved fit? As suggested by Coibion-Gorodnichenko, when private-sector and central bank forecasts differ there is an automatic gradualism to rate-setting similar to the role played by inertial terms in estimated Taylor rules. In the nowcasting version (5) the central bank responds systematically to their forecasts for inflation and the output gap, to their uncertainty about those forecasts, and to private-sector forecasts. This policy rule encompasses factors believed to affect real-time policy making: uncertainty and a fear of falling behind-the-curve when private-sector expectations become unanchored from the central bank's forecasts. For these reasons, the nowcasting rule (5) provides an improved fit to historical policy rates.

5.4 A Forward-looking Rule with Uncertainty

In practice, there is often a lag between the time policy rates are set and when inflation or output are affected by the policy action. When such policy lags exist, it is often recommended that interest rate rules react to forecasts of future economic variables. This section estimates a general forward-looking Taylor-type rule of the form:

$$i_t = (1 - \rho)\hat{i}_t + \rho i_{t-1} + \varepsilon_t \tag{6}$$

$$\hat{i}_t = \alpha_0 + \alpha_\pi E_t \pi_{t+1} + \alpha_x E_t x_{t+1} + \alpha_{\sigma_\pi} \hat{\sigma}^2_{\pi,t+1} + \alpha_{\sigma_x} \hat{\sigma}^2_{x,t+1} + \alpha_g g_t \tag{7}$$

The rule (6) includes a partial adjustment equation and a targeting equation that depends on the forecasted values for inflation and the output gap in the following quarter, given the information available in the current quarter, the forecast uncertainty for those variables, and real GDP growth. This rule is motivated, in part, by **?**. The forecasts and forecast uncertainty measures are taken as the median forecast and median uncertainty, respectively, computed from the individual histograms for one-quarter ahead forecasts. These histograms can be computed directly from one-step ahead projections of the current quarter histograms whose construction was discussed earlier.

Table 6 reports the results from a least-squares regression of the forward-looking rule (6). The policy coefficients feature the familiar finding of an (expected) inflation reaction coefficient greater than one and a strong reaction to forecasted output gaps. The size of the inflation reaction coefficient is in line with the variants of the nowcasting Taylor rule presented above. The sign on the inflation and output forecast uncertainty reaction coefficient continues to be negative. The forward-looking rule is consistent with policy being cautious against low inflation and low output outcomes. The coefficient on output growth is now significant.

The results from Table 6 indicate the role of uncertainty in the policy-making process is robust to forward-looking policy rules. The fit of the rule is comparable to the inertial nowcasting rule.[17]

6 Conclusion

This paper reconsiders the empirical fit of the Taylor rule by replacing contemporaneous inflation and the output gap as indicators with "nowcasts" that depend on the point forecast and a precautionary term that reflects forecast uncertainty. Nowcasts are empirically identified in the Survey of Professional Forecasters. Including forecast uncertainty can explain the "too low for too long" puzzle in the following sense. The subjective probability distributions during the 2003-2004 period shifted towards greater uncertainty about the inflation rate and that uncertainty was skewed towards inflation rates below 1% leading the Federal Reserve to be overly cautious about raising rates.

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[17]The results in Table 6 do not include real GDP or forecast differences as explanatory variables. A comparable specification for the inertial nowcasting rule leads to an adjusted $R^2 = 0.971$ versus an adjusted $R^2 = 0.967$ for the forward-looking rule.

7 Appendix

This appendix discusses estimation of the individual histograms.

Denote x_{qt} as the target variable (inflation, output growth) in quarter q in year t. Each forecaster i has a model that places probabilities p^i_{jqt} that the variable x will take a value j in period t. These probabilities define the individual histograms from which the moments can be calculated. The SPF, however, solicits forecasts about the year-over-year average value of x_t, denoted as $\bar{x}_t$. It is from the reported histograms for $\bar{x}_t$ that we infer the quarterly probabilities p^i_{jqt}. Denote Ω_{qt} as the observed values of of x in quarter q. It follows that the forecast horizon depends on q: $q = 3$ implies a forecast horizon of two quarters, $q = 2$ implies a three quarter horizon, and $q = 1$ implies a four quarter horizon.

To compute the quarterly forecast probabilities, note that forecasters report $Pr(\bar{x}_t \in b_j|\Omega_{qt})$, which is a non-linear function of the various values for x_{qt}. Following **?** and **?**, one can approximate $\bar{x}_t$ as an average of quarterly forecasts:

$$\bar{x}_t = .25x_{4t} + .5x_{3t} + .75x_{2t} + x_{1t} + .75x_{4t-1} + .5x_{3t-1} + .25x_{2t-1}$$

Thus, the SPF data provide

$$Pr\left(.25x_{4t} + .5x_{3t} + .75x_{2t} + x_{1t} + .75x_{4t-1} + .5x_{3t-1} + .25x_{2t-1} \in b_j|\Omega_{qt}\right)$$

The identifying assumption is that forecasters assume that $x_{q't}, q' > q$ follows a random-walk Markov chain. By interpreting $x_{q't}$ as the incremental value to $\bar{x}_t$ straightforward calculations lead to expressions for $Pr(\bar{x}_t \in b_j|\Omega_{qt})$ as a function of the time and spatially homogeneous transition probabilities. If p_j is the probability that the increment $x_{q't} = j$, then simple (though, tedious) calculations can compute the probabilities for each vertex along all possible paths of the random walk. For example, in the third quarter of year t, there are 10 possible values for x_{3t} and then 100 possible increments for (x_{3t}, x_{4t}). The probabilities attached to these vertices can then be collected to compute $Pr\left(\bar{x}_t \in b_j|\Omega_{qt}\right)$. Then setting $Pr\left(\bar{x}_t \in b_j|\Omega_{qt}\right)$ equal to the SPF histogram for a given forecaster leads to a system of 10 non-linear equations in the 10 probabilities. This procedure produces the quarterly probabilities for a given forecaster i in quarter q of year t, i.e. p^i_{jqt}. The estimation procedure is repeated across all i, q, t.

Since the survey respondent's probability is attached to a bin, rather than a number, some assumption needs to be made on how the reported probability is distributed across the bin. In the results reported, we assume that all weight is placed on the lower end point of the bin. We treat this as the benchmark case, though, we note that all qualitative results are robust to the weight being placed on the midpoints with only small quantitative differences.

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Figure 1: Taylor Rule. Dashed line is the actual federal funds rate, the solid line is the federal funds rate recommended by the Taylor rule.
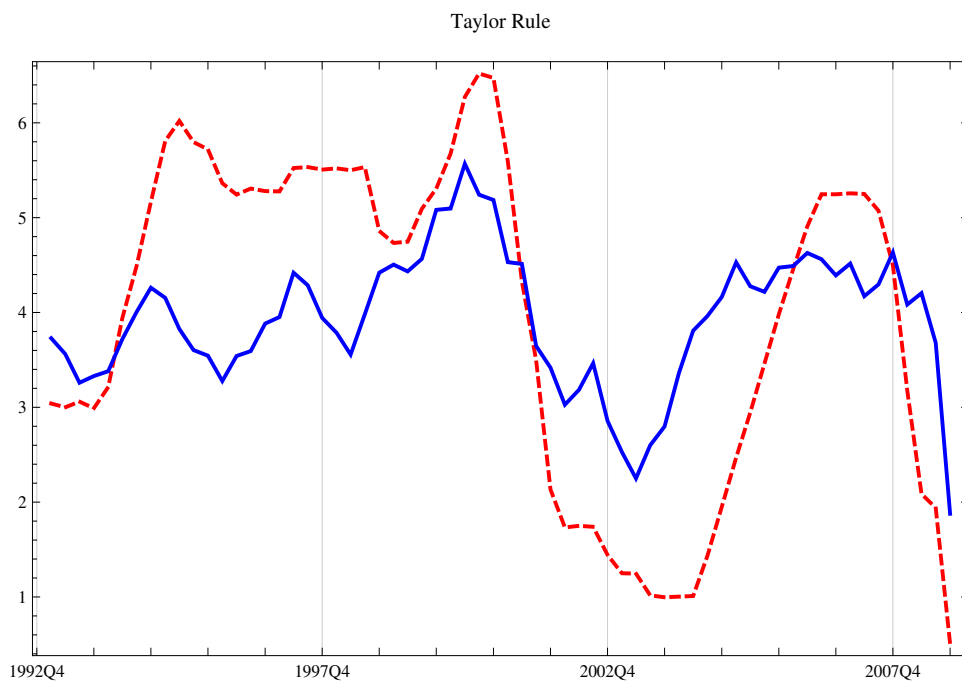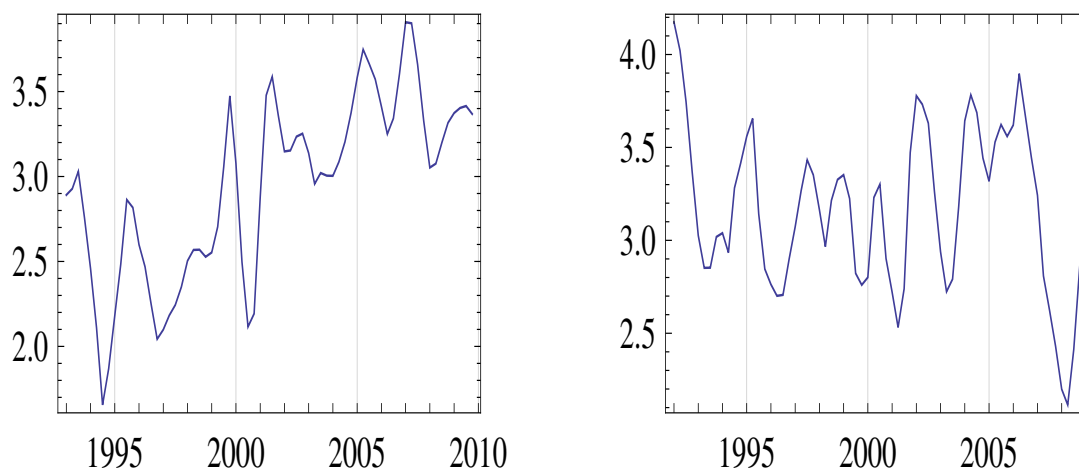
Taylor Rule

Figure 2: Median Uncertainty in the SPF

Figure 3: Distribution of Uncertainty in the SPF

Figure 4: Skewness

SPF Inflation Skew

SPF Growth Skew
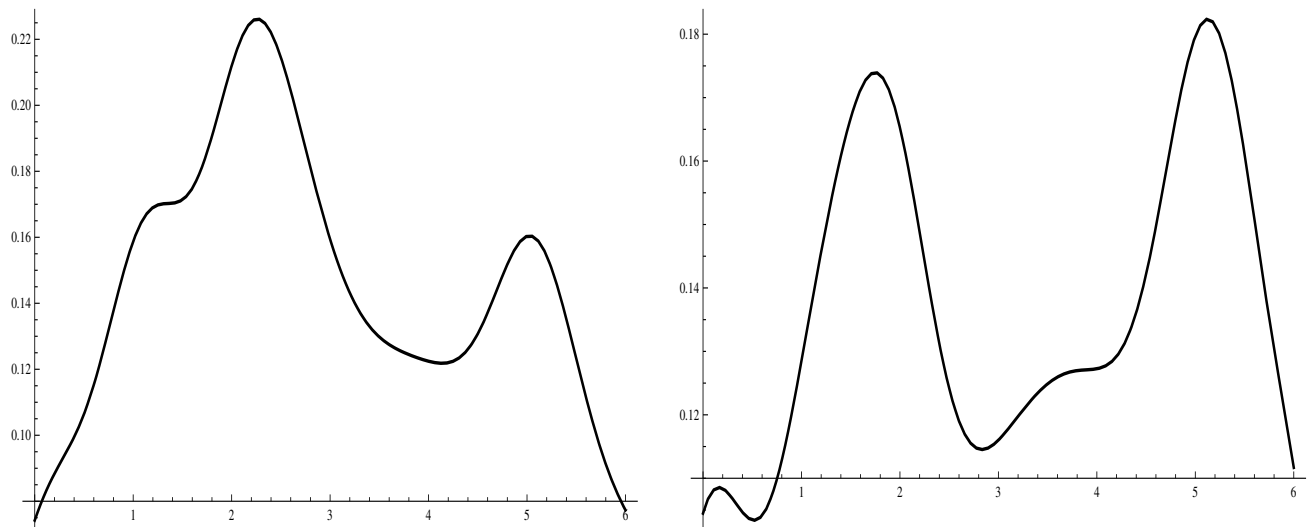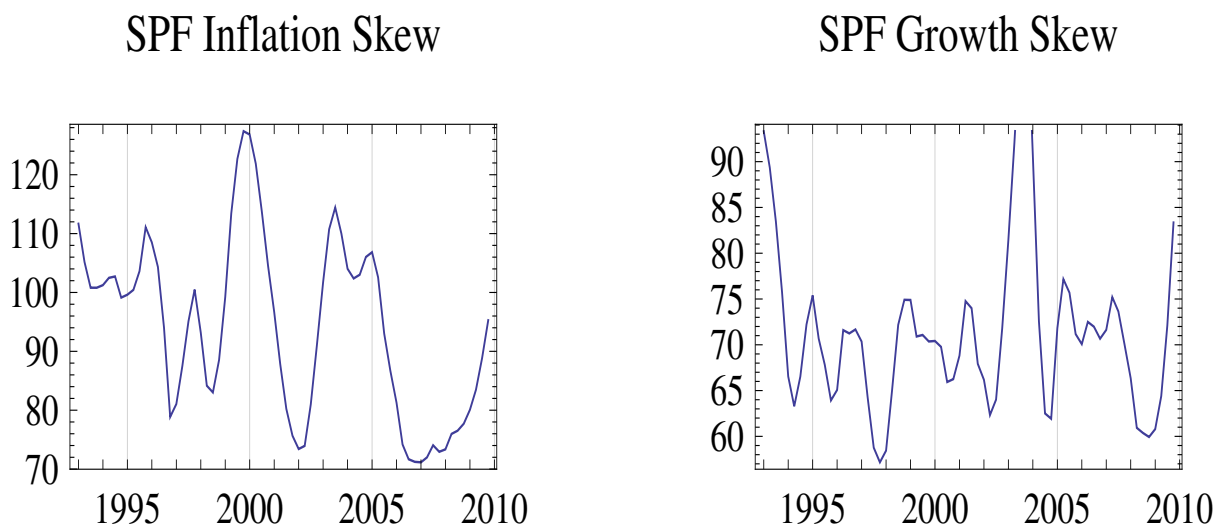
Figure 5: Taylor Rule versus nowcasting Taylor Rule. Solid line is the nowcasting Taylor rule, the dotted line is the Taylor rule, and the dashed line is the actual federal funds rate.
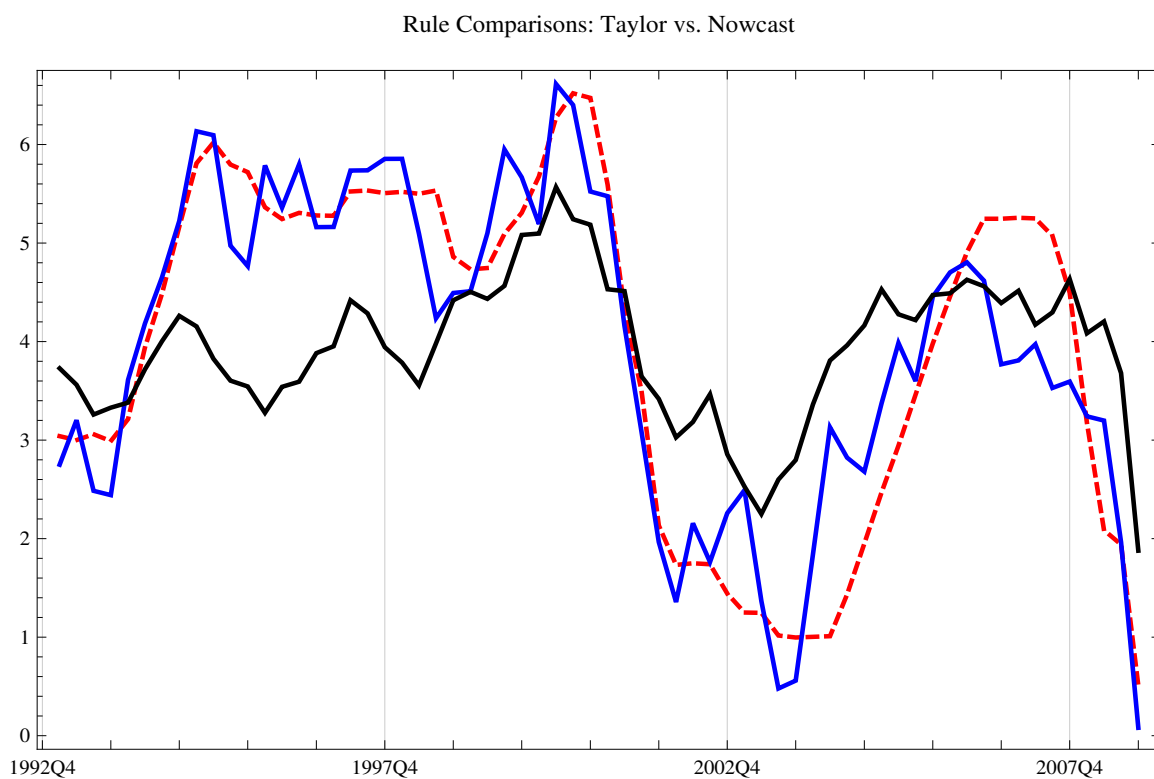
Rule Comparisons: Taylor vs. Nowcast

Figure 6: Estimated Taylor Rules versus Estimated Nowcast Taylor Rule. Solid line is the nowcasting Taylor rule, the dotted line is the Taylor rule, and the dashed line is the actual federal funds rate.
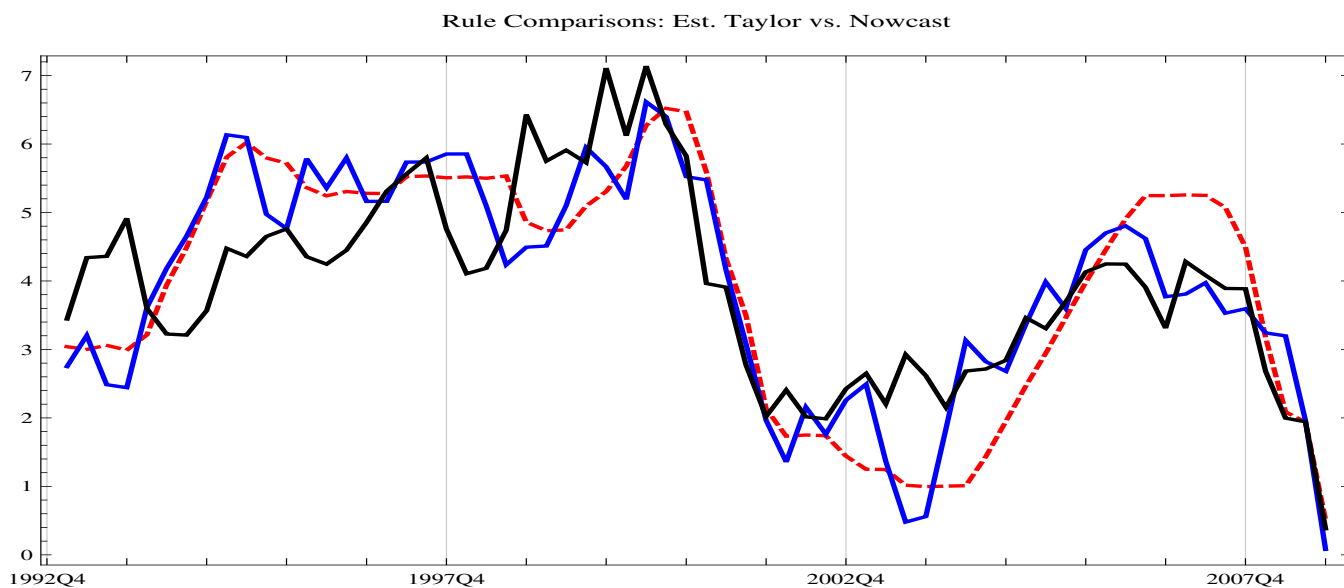
Rule Comparisons: Est. Taylor vs. Nowcast

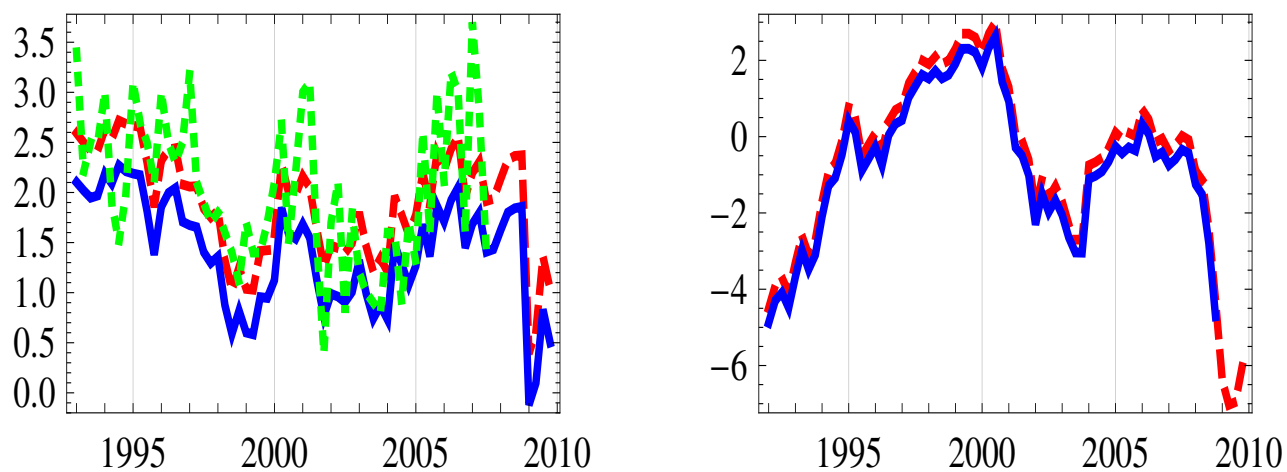Figure 7: Nowcasts. Solid line are the nowcasts, the dotted line are the forecasts.

Figure 8: Inertial Nowcast Taylor Rule. Solid line is the nowcasting Taylor rule and the dashed line is the actual federal funds rate.
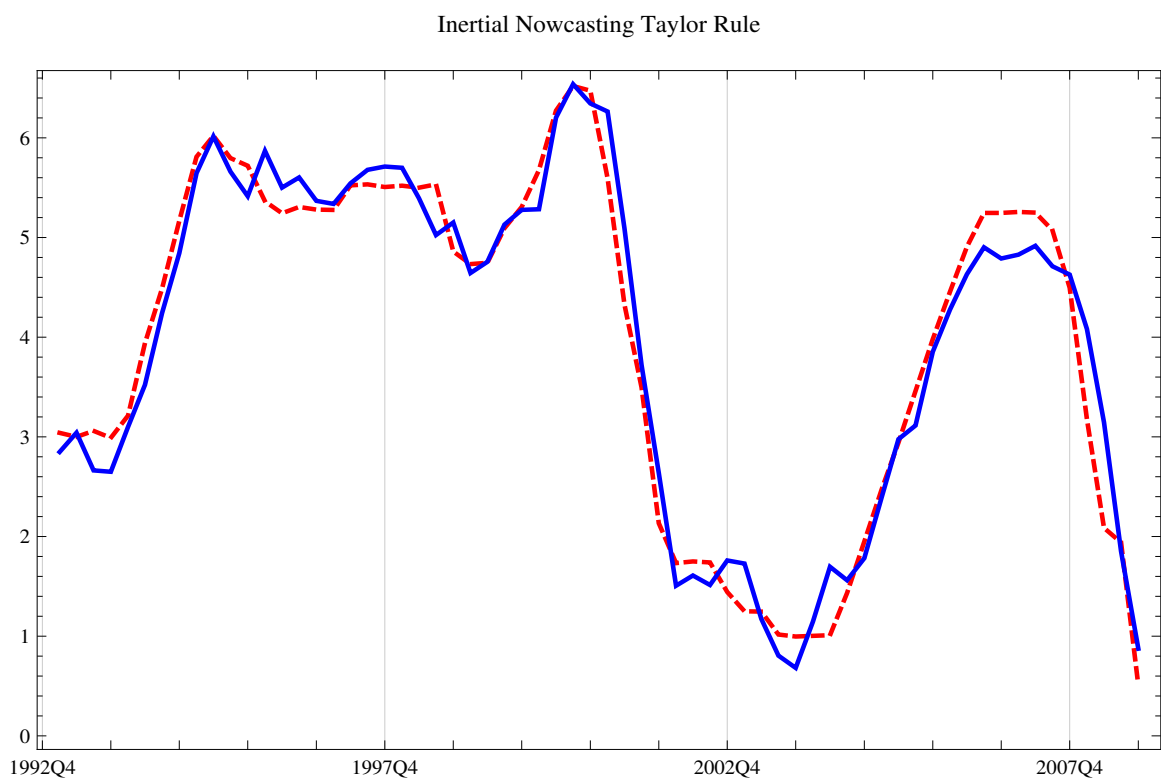
Inertial Nowcasting Taylor Rule

Table 1: Taylor Rule: Estimation Results (Newey-West standard errors in parentheses).

	Taylor rule	Taylor rule with real-time data	Taylor rule with Greenbook forecasts
α_0	0.17 (1.56)	0.77 (0.78)	1.81 (0.36)
α_π	1.94 0.78)	1.27 (0.29)	1.074 (0.37)
α_x	0.82 (0.12)	0.71 (0.12)	0.76 (0.07)
$\bar{R}^2$	0.44	0.62	0.73

Table 2: Nowcasting Taylor Rule: Estimation Results (Newey-West standard errors in parentheses).

	SPF Nowcast Taylor rule	Nowcast Taylor rule
α_0	1.18 (0.58)	4.60 (1.03)
α_π	2.34 (0.25)	1.73 (0.17)
α_x	0.64 (0.16)	0.85 (0.05)
α_{σ_π}	–	−0.99 (0.39)
α_{σ_x}	–	−0.35 (0.31)
$\bar{R}^2$	0.51	0.81

Table 3: Inertial Nowcasting Taylor Rule: Estimation Results (Newey-West standard errors in parentheses).

	Real-time Taylor rule	Nowcast Taylor rule	Nowcast Taylor Rule with AR(2) smoothing
α_0	-2.37 (0.20)	5.75 $(.44)$	5.78 $(.57)$
α_π	2.53 (0.09)	2.27 $(.12)$	1.76 (0.12)
α_x	1.12 (0.04)	1.03 $(.05)$	0.88 (0.04)
α_{σ_π}	$-$	-1.07 (0.12)	-1.20 (0.10)
α_{σ_x}	$-$	-1.03 $(.16)$	-0.57 (0.14)
ρ	0.83 (0.05)	0.67 $(.05)$	1.29 (0.12)
ρ_2	$-$	$-$	-0.53 $(.10)$
$\bar{R}^2$	0.94	0.96	0.97

Table 4: Taylor Rules Including Real GDP Growth: Estimation Results (Newey-West standard errors in parentheses).

	Real-time Taylor rule	Nowcast Taylor rule
α_0	1.04 (0.47)	4.84 (1.6)
α_π	1.32 (0.19)	1.72 (0.21)
α_x	0.79 (0.07)	0.85 (0.06)
α_{σ_π}	–	−1.02 (0.25)
α_{σ_x}	–	−0.37 (0.37)
α_g	−0.31 (0.11)	−0.05 (0.09)
$\bar{R}^2$	0.65	0.78

Table 5: Nowcasting Taylor Rule with Forecast Differences: Estimation Results (Newey-West standard errors in parentheses).

α_0	4.56 (0.93)
α_π	1.73 (0.16)
α_x	0.82 (0.05)
α_{σ_π}	−0.75 (0.34)
α_{σ_x}	−0.52 (0.33)
$\alpha_{\triangle_{\pi e}}$	−1.43 (0.19)
$\alpha_{\triangle_{x e}}$	−0.10 (.06)
$\bar{R}^2$	0.82

Table 6: Forward-looking Taylor Rule with Forecast Uncertainty and Real GDP Growth: Estimation Results (Newey-West standard errors in parentheses).

α_0	0.03 (3.13)
α_π	2.45 (0.25)
α_x	1.02 (0.24)
α_{σ_π}	-0.61 (0.31)
α_{σ_x}	-0.49 (0.11)
α_g	0.43 (0.07)
ρ	0.73 (0.37)
$\bar{R}^2$	0.96