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A Comparison of the In-Sample and Out-of-Sample Properties of Linear and Nonlinear Taylor Rules Using Real-Time Data

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Abstract

This paper examines the in-sample and out-of-sample properties of linear and nonlinear Taylor rules using real-time U.S. data. We find that (i) in-sample and out-of-sample performance measures generally select the same functional form for the Taylor rule and that (ii) the form of the Taylor rule differs across the pre-Greenspan and Greenspan sample periods. However, when we compare the out-of-sample forecasting performance of the Taylor rules to those of univariate models of the federal funds rate, we find it quite interesting that the univariate models forecast better than the Taylor rules after 1979 (but not before 1979).

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Taylor's (1993) celebrated work shows that a simple rule, in which the short-term nominal interest rate reacts linearly to deviations of inflation and output from their target levels, provides a good description of actual monetary policy in the United States. The importance of a simple characterization of the conduct of Federal Reserve policy is evidenced by the fact that, at the time of this writing, Econlit lists 151 papers with the phrase "Taylor Rule" in the title and/or abstract. The original specification of the rule took the form:

$$i_t^* = r^* + \pi_t + \beta_\pi(\pi_t - \pi^*) + \beta_y y_t \tag{1}$$

where i_t^* is the target short-term nominal interest rate for quarter t, r^* is the equilibrium real interest rate, π_t is the inflation rate, π^* is the inflation target, and y_t is the output gap measured by the deviation of real output from its potential level.

When π^* and r^* were set equal to two and β_π and β_y were set equal to one half, Taylor (1993) found that equation (1) provided a good description of the behavior of the federal funds rate over the 1987 − 1992 period. He also claimed that this rule could be a useful guideline for future monetary policy.

Many subsequent papers have been written with the aim of obtaining the most appropriate form of the Taylor rule. Clarida, Gali, and Gertler (1998, 2000), Woodford (1999), Goodhart (1999), Levin et al. (1999), and Amato and Laubach (1999) generalized equation (1) to allow for lagged values of the federal funds rate. The lags were statistically significant, purged all serial correlation from the residuals, and provided evidence that the Federal Reserve acts to smooth the time path of interest rates. Huang et al. (2001) and Orphanides (2003) showed that a forward-looking rule performed better than a backward-looking rule and that a forward-looking rule was a good indicator of ensuing monetary policy. Levin et al. (1999) and Taylor (1999a) found that the rule was robust in that it performed well in a number of different macroeconomic settings.

More recently, it has been argued that a nonlinear specification for the Taylor rule might be more appropriate than a linear one. Nobay and Peel (2003), Cukierman and Gerlach (2003), Gerlach (2003), Ruge-Murcia (2002, 2004), Bec et al. (2002), Dolado et al. (2002) and Surico (2004) argue that central bank preferences are not symmetric in inflation and/or the output gap. If, for example, the Fed is more concerned about high inflation than low inflation, the response of i_t^* is likely to be more dramatic when the inflation is above the target than when inflation is below the target. As a result, the optimal feedback rule will not be linear in π_t. Schaling (1999) and Dolado et al. (2005) provide a second rationale for a nonlinear Taylor rule. If the aggregate supply curve is convex, so that there is a nonlinear relationship between output and inflation, the optimal feedback rule relating interest rates to output and inflation should also be nonlinear. They estimate several nonlinear feedback rules and conclude that nonlinear rules fit the data better than linear ones.

Given the proliferation of Taylor rules, it is not clear which one provides the best model of the federal funds rate. As such, one aim of the paper is to compare the in-sample and the out-of-sample properties of linear and nonlinear Taylor rules using real-time U.S. data. Although the in-sample performance of the alternative Taylor rule specifications is important, there is a large literature—see Clements and Hendry's (1998) excellent survey—indicating that out-of-sample forecasting performance can be a useful aid in selecting among alternative functional forms. As illustrated by Swanson and White (1997), Rothman (1998), and Liu and Enders (2003), out-of-sample forecasts can be especially useful for model selection when working with nonlinear models because of the enhanced possibilities for overfitting the data.

A second aim of the paper is to provide a comprehensive look of the in-sample properties of the policy rules using real-time data. To our knowledge, previous studies on nonlinear Taylor rules employ only *ex post* data. However, as pointed out by Orphanides (2000, 2003, 2004), it is better to use real-time data when examining the Taylor rule. The reason is that inflation and the output gap are subjected to constant revisions. The *ex post* data might be quite different from the data that were actually available to the Fed at the time when they set the federal funds rate.

The paper is organized as follows. Section 1 presents the seven models employed in this paper (five popular econometric specifications of the Taylor rule and two univariate models of the federal funds rate). Section 2 discusses the nature and sources of the real-time data used in the empirical sections of the paper. In section 3, we estimate the seven models using quarterly U.S. data and compare the in-sample fit of each. We find some evidence that the Fed followed the "Taylor principle" before 1979, but it is not robust to different rule specifications. We also find nonlinearity in the Fed's behavior after 1979, and it seems that the nonlinearity reflects the Fed's behavior during the Paul Volcker era rather than the Greenspan era. The in-sample measures (the Akaike Information Criteria (*AIC*) and the Bayesian Information Criteria (*BIC*)) suggest that the linear forward-looking rule and one nonlinear rule are the most appropriate forms of the Taylor rule. In section 4, we compare the out-of-sample forecasting performance of the seven models. We find that among all the policy rule models, the out-of-sample measures generally select the same specifications as the in-sample measures: the linear forward-looking rule and one nonlinear rule. However, when we compare the out-of-sample performance of the policy rules to those of the two univariate models, we find it quite interesting that the univariate models forecast better than the policy rules after 1979 (but not before 1979). Concluding remarks are contained in section 5.

1. Taylor Rule Variants

A number of different versions of the Taylor rule have appeared in the literature. Rearranging equation (1) we obtain the simplest version of the Taylor rule:

$$i_t^* = \alpha + \theta_\pi \pi_t + \beta_y y_t \qquad (2)$$

where $\alpha = r^* - \beta_\pi \pi^*$ and $\theta_\pi = 1 + \beta_\pi$.

The difficulty with equation (2) is given by Orphanides (2000, p4.): "…rules [that] rely on within-quarter reactions to data about that quarter are not operational since the data needed for the rule are not available within the quarter." The values of π_t and y_t are not released by the BEA until after quarter t is over, so the Fed does not know the values of π_t and y_t at the time they set the value of i_t^*. As a result, the Taylor rule has been operationalized either by specifying that policy reacts to lags of inflation and the output gap (the backward-looking rule) or by using forecasted values of inflation and output gap (the forward-looking rule). Equations (3) and (4) characterize the backward-looking rule and the forward-looking rule, respectively:

$$i_t^* = \alpha + \theta_\pi \pi_{t-k} + \beta_y y_{t-k} \qquad (3)$$

$$i_t^* = \alpha + \theta_\pi E_t \pi_{t+k} + \beta_y E_t y_{t+k} \qquad (4)$$

In equation (3), $k > 0$. In equation (4), $k \geq 0$ (k =0 means that the interest rate reacts to within-quarter forecasts of inflation and output). Forward-looking rules capture the ability of the Fed to set the current value of the interest rate based on the expected future time path of the economy. In this way, the Fed can pre-empt undesirable changes in inflation and/or the output gap. Empirical studies generally find that forward-looking rules have better in-sample properties than backward-looking rules.

There is substantial evidence (see Clarida et.al. (2000), for instance) that that the Federal Reserve acts to smooth the adjustment of the interest rate to its target value. As a result, the actual federal funds rate for quarter t, i_t, evolves toward its target value with a degree of inertia:

$$i_t = (1 - \rho)\, i_t^* + \rho(L)\, i_{t-1} + \varepsilon_t \qquad (5)$$

where $\rho(L) = \rho_1 + \rho_2 L + \ldots + \rho_n L^{n-1}$ and $\rho \equiv \rho(1)$. The magnitudes of the values of ρ_i reflect the degree of smoothing. Large values of ρ are associated with a slow speed of adjustment of the federal funds rate to the target level. Empirical studies generally find that the lag length $n = 2$ and that ρ is highly significant.

In order to find the most appropriate specification for the Taylor rule, we estimate five different popular functional forms. Following previous literature, we employ 2 lagged interest terms. Model 1 is the backward-looking Taylor rule, where the policy reacts to the previous quarter's inflation and output gap:[1]

Model 1. $i_t = (1 - \rho)(\alpha + \theta_\pi \pi_{t-1} + \beta_y y_{t-1}) + \rho_1 i_{t-1} + \rho_2 i_{t-2} + \varepsilon_t$ where $\rho_1 + \rho_2 = \rho$.

Model 2 is the forward-looking rule and model 3 is the within-quarter rule:

Model 2. $i_t = (1 - \rho)(\alpha + \theta_\pi E_t \pi_{t+1} + \beta_y E_t y_t) + \rho_1 i_{t-1} + \rho_2 i_{t-2} + \varepsilon_t$ where $\rho_1 + \rho_2 = \rho$.

Model 3. $i_t = (1 - \rho)(\alpha + \theta_\pi E_t \pi_t + \beta_y E_t y_t) + \rho_1 i_{t-1} + \rho_2 i_{t-2} + \varepsilon_t$ where $\rho_1 + \rho_2 = \rho$.

In model 2, the policy reacts to 1-quarter-ahead forecasts of the inflation and the within-quarter forecasts of the output gap. Orphanides (2004) uses this specification as the forward-looking rule. (It might be natural to use $E_t y_{t+1}$ instead of $E_t y_t$, but, as discusses in section 2, the real-time data of $E_t y_{t+1}$ are not available.) In model 3 the policy reacts to within-quarter forecasts of both the inflation and the output gap.

Models 4 and 5 are nonlinear specifications of the Taylor rule. The nonlinear specifications allow for the possibility that the Federal Reserve behaves differently when the fed funds rate is high than when it is low. The most popular nonlinear specifications are some form of the logistic or the exponential smooth transition model. Both specifications are a form of

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[1]We also used Taylor's (1993) original specification that ignores the interest rate smoothing terms. The results are not reported here since this version of the rule performed poorly.

regime-switching model in that they allow the intensity of the Fed's response to vary with the state of the economy.

Model 4 is a logistic generalization for the forward-looking version of the Taylor rule. We employ the forward-looking version because, as mentioned earlier, forward-looking rules generally perform better than backward-looking rules in empirical literature.[2]

Model 4. $i_t = \alpha_0 + \alpha_1 E_t \pi_{t+1} + \alpha_2 E_t y_t + \alpha_3 i_{t-1} + \alpha_4 i_{t-2} + \theta(\beta_0 + \beta_1 E_t \pi_{t+1} + \beta_2 E_t y_t + \beta_3 i_{t-1} + \beta_4 i_{t-2}) + \varepsilon_t$

where $\theta = \{1 + \exp[-\gamma(i_{t-1} - c)]\}^{-1}$, $\gamma \geq 0$.

Notice that θ increases from 0 to 1 as the value of $(i_{t-1} - c)$ increases throughout its range. Hence, as long as γ and the various β_i differ from zero, the federal funds rate will behave differently for small values of $(i_{t-1} - c)$ than for large values. For $\theta \cong 0$, the inflation and output responses of the fed funds rate are α_1 and α_2 while for $\theta \cong 1$ the same responses are $\alpha_1 + \beta_1$ and $\alpha_2 + \beta_2$, respectively. Notice that positive values of β_1 and β_2 imply that the Federal Reserve responds more aggressively to inflation and the output gap when i_{t-1} is high than when it is low. As discussed in Enders (2004), γ is the "smoothness" parameter. If $\gamma = 0$, the model becomes linear. However, large values of γ mean that the transition between regimes becomes very sharp for any given change in $(i_{t-1} - c)$. A very large value of γ is equivalent to a 2-regime threshold model. For convenience of estimation, we do not impose the $(1-\rho)$ and $\rho(L)$ form although the values of θ_π and β_y can be easily recovered. For example, θ_π can be recovered through the relationship $\theta_\pi[1 - (\alpha_3 + \theta\beta_3) - (\alpha_4 + \theta\beta_4)] = \alpha_1 + \theta\beta_1$.

Model 5 is the exponential specification of the Taylor rule:

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[2] For both the exponential and logistic models, the residual sums of squares using i_{t-d} for $d > 1$ as the threshold variable were above those using those using π_{t-1}. Also, for both specifications, we allowed the threshold variable to be y_{t-1} and to be π_{t-1}. However, to save space, these variants are not reported here since they performed badly on several grounds.

Model 5. $i_t = \alpha_0 + \alpha_1 E_t \pi_{t+1} + \alpha_2 E_t y_t + \alpha_3 i_{t-1} + \alpha_4 i_{t-2} + \theta(\beta_0 + \beta_1 E_t \pi_{t+1} + \beta_2 E_t y_t + \beta_3 i_{t-1} + \beta_4 i_{t-2}) + \varepsilon_t$

where $\theta = 1 - \exp[-\gamma(i_{t-1} - c)^2]$, $\gamma \geq 0$.

In the exponential specification, the federal funds rate will behave differently for small values of $(i_{t-1} - c)^2$ than for large values. Notice that the specification for θ in model 5 implies that the Taylor rule is symmetric around the point $i_{t-1} = c$. Instead, if the Federal Reserve has asymmetric preferences, it might be preferable to use the logistic specification.

We compare these 5 Taylor-rule-type models to two simple univariate models of the federal funds rate. Model 6 is the univariate AR(2) model:

Model 6. $i_t = \alpha_0 + \alpha_1 i_{t-1} + \alpha_2 i_{t-2} + \varepsilon_t$

We experimented with a more general AR(p) specification but longer lags were not statistically significant and shorter lags always resulted in regression residuals exhibiting substantial serial correlation. Since interest rates have been found to act as unit-root processes, we also estimate model 6 constraining $\alpha_1 + \alpha_2 = 1$ so as to obtain the autoregressive AR(1, 1) model reported as model 7:

Model 7. $\Delta i_t = \alpha_0 + \alpha_1 \Delta i_{t-1} + \varepsilon_t$

2. The Data

As discussed in Orphanides (2000, 2003, 2004), it is desirable to use real-time data to examine the Taylor rule since inflation and output data are subjected to constant revisions. The most recent data might be quite different from the data that were available to the Fed when they set the interest rate. As such, we use the Orphanides (2004) real-time data of inflation and output gap in this paper. The time span of the data is 1966:Q1-1995:Q4. The data contain the real-time lags and the real-time forecasts of inflation rate and the output gap. The inflation forecasts (i.e.,

$E_t\pi_{t+k}$) are available for up to 5 quarters ahead, while only within-quarter forecasts are available for the output gap. The inflation rate is defined as the difference of the logarithm of the GDP deflator, and the output gap is defined as the difference of the logarithm of actual GDP and the logarithm of the potential GDP. We divide the whole sample around 1979:Q3, corresponding to the appointment of Paul Volcker as the Federal Reserve Chairman, because it has been suggested in the previous literature that U.S. monetary policy was conducted in significantly different ways before 1979 and after 1979 (see Hakes (1990), Judd and Rudebusch (1998), and Pakko (2005), for instance). Also, because values for $E_t\pi_{t+1}$ are missing in 1966:Q2 and 1966:Q4, we begin our sample with 1967:Q1 rather than 1966:Q1. This leaves two sub-sample periods for us to examine: 1967:Q1-1979:Q2 and 1979:Q3-1995:Q4.

Clearly, it is also of interest to examine the Taylor rule for the entire Greenspan era. However the Orphanides (2004) data set does not allow us to do this since it runs only through 1995:Q4.[3] As such, we obtain the quasi real-time data of the output gap developed by Van Norden. Van Norden's data are constructed by detrending the real-time real GDP (See the link http://www.hec.ca/pages/simon.van-norden/codepage.html for details) and has been employed by Orphanides and Van Norden (2005) and Österholm (2005). We extended Van Norden's data set (which ends at 2003:Q2) to 2005:Q4. The real-time real GDP data are obtained from the Philadelphia Federal Reserve Board's Real Time Data Archive.

It is well-known that during the Greenspan period, the Federal Reserve favored the Core Personal Consumption Expenditures price index for the measure of inflation.[4] As such, we construct the inflation rate using the core PCE deflator during the period 1987:Q4–2005:Q4.

[3] In the original version of this paper we used a single ex-post data set running from 1954:Q3 through 2003:Q4. However, in this version, we wanted to use real-time data. Unfortunately, it is not possible for us to update the Orphanides' (2004) real-time data past 1995:Q4 as he states that the construction methods and assumptions used to create his data set varied over time. To avoid being ad hoc, we use his exact data set.

[4] We thank one of the referees for making this point.

Unfortunately, we only have the *ex post* data of this inflation measure. However, it is also well-known that revisions in the output gap estimates can be substantial whereas revisions in inflation are minor in comparison (See Orphanides (2001), for instance). Therefore, it seems reasonable to assume that the use of the *ex post* inflation data will have negligible influence on our results. We use the quasi real-time output gap (y_t) and the *ex post* inflation data constructed from core PCE deflator (π_t) when we estimate the policy rules over the 1987:Q4 – 2005Q4 period.

3. In-Sample Estimates of the Alternative Models

In this section, we examine the in-sample estimates of the 5 specifications of the Taylor rule and the 2 univariate models. We estimate the 7 models over 1967:Q1-1979:Q2 and 1979:Q3-1995:Q4 using Orphanides (2004) data, and over 1987:Q4-2005:Q4 using the quasi real-time data. The Taylor rule models are estimated using nonlinear least squares (NLLS) over the first two periods and using GMM over the last period. Because we do not have the data of $E_t\pi_{t+1}$ and E_ty_t during the last period, we replace $E_t\pi_{t+1}$ and E_ty_t by the actual realizations of π_{t+1} and y_t and use GMM to estimate models 2, 3, 4, and 5 (See Clarida, et al. (2000) for similar methodology). Following Clarida, et al. (2000), we use lags of the Funds rate, inflation, output gap, and M2 growth as instruments.

Tables 1 through 3 report the estimation results of the seven models for the three sample periods. The standard measures of in-sample fit represented by the Akaike Information Criteria (*AIC*) and the Bayesian Information Criteria (*BIC*) are reported in the last two columns of the tables. Notice that models 2 and 4 have the best fit for the pre-Volcker period. Model 2 (the forwarding-looking rule) has the smallest *BIC* and the second-smallest *AIC*, while Model 4 (the logistic model) has the smallest *AIC* and the second-smallest *BIC*. The backward-looking rule and the two univariate models perform poorly. The exponential specification does not perform well in that it has the largest *BIC*.

Over the second period, the *AIC* and *BIC* both select the logistic model to be the best-fitting model. The exponential model performs well according to *AIC* but not *BIC*. Among the linear models, the *AIC* and *BIC* both select the forward-looking rule. As before, the backward-looking rule and the two univariate models perform poorly.

The situation is quite different for the Greenspan period in that *BIC* selects the univariate AR(2) model while *AIC* selects the exponential model. The forward-looking rule also performs very well in that it has the second-smallest *AIC* and *BIC*. However, the logistic and backward-looking models fare poorly.

The key point is that the forward-looking rule performs consistently well across three periods. The logistic rule performs very well over the first 2 periods but not the last period. The univariate models fare poorly over the first 2 periods but they perform quite well over the last period. These rankings do not change in any important way when we purge the over-parameterized nonlinear models of statistically insignificant coefficients. The rankings are also quite robust to reasonable variants in the starting dates. Overall, the in-sample performance measures select the forward-looking rule and the logistic rule to be the best rule specifications: the forward-looking rule fares best during the first and the third periods and a nonlinear logistic rule is the best over the second period.

The Taylor Principle

There is a debate in the literature about whether the Fed followed the "Taylor principle" before and after 1979. The "Taylor principle" states that a successful monetary policy requires that the nominal interest rate responds more than proportionally to a change in the inflation. In essence, the Fed must increase the real interest rate to combat inflation. As such, the value of θ_π

must exceed unity for monetary policy to be stabilizing. Previous empirical studies on the "Taylor principle" produced mixed results. For example, Clarida, et al. (2000) estimated a forward-looking policy rule using *ex post* data and found that the estimated value of θ_π is less than one during the pre-Volcker period but greater than one during the Volcker-Greenspan period. They conclude that during the Great Inflation the Fed did not follow the "Taylor principle" and pursued a policy that accommodated inflation and induced instability. However, when Orphanides (2004) estimated a forward-looking rule using real-time data the estimated value of θ_π was greater than one both before and after 1979. He suggests that the monetary policy during the Great Inflation was not accommodative. The instability of the economy during the Great Inflation was the outcome of the Fed's misperception of the state of the economy.

Our estimation results suggest that the estimated value of θ_π is sensitive to different rule specifications over the pre-Volcker period. Specifically, Table 1 indicates that the values of θ_π from Models 1 through 3 are 0.604, 1.355 and 0.824, respectively. However, since the fit of the forward-looking rule dominates that of the other two, there is reasonable evidence supporting the view that the Fed followed the Taylor principle during the pre-Volcker period. This result is reinforced by the nonlinear estimate of the logistic model (the best fitting of the nonlinear models). The logistic analog of θ_π is 2.376 when $\theta = 0$ (so that i_{t-1} is far below the threshold value of 10.043) and is 3.351 when $\theta = 1$ (so that i_{t-1} is far above the threshold value). Even though these magnitudes seem large, they provide additional evidence that the Fed followed the "Taylor principle" before 1979.[5]

In contrast, the estimated values of θ_π are greater than one for all three linear specifications over the Volcker-Greenspan period, regardless of whether the Orphanides (2004)

[5] In the logistic and exponential specifications, the 'feedback' coefficient on inflation is $(\alpha_1 + \theta\beta_1)/[\ 1 - (\alpha_3 + \theta\beta_3) - (\alpha_4 + \theta\beta_4)\ ]$. The hallmark of these models is that this feedback magnitude depends on the level of the threshold variable.

data or the quasi real-time data are employed. For example, over the second period, the estimated value of θ_π for the within-quarter model is 1.639 and the range for the logistic model (the best fitting nonlinear model) is 1.275 to 2.528. For the Greenspan period, the linear estimates of θ_π are all clustered between 1.3 and 1.4. The nonlinear analog of θ_π for the exponential model (the best fitting nonlinear model for this period) are problematic in that the range is from –0.568 to 2.027. Nevertheless, since the exponential model has the best fit (as measured by the *AIC*), we turn to the out-of-sample forecasts to aid in model selection.

4. Out-of-Sample Fit

Although the in-sample performance of different Taylor rule specifications is important, out-of-sample forecasting performance can be a useful aid in selecting among alternative policy rule specifications. This is particularly true since the *AIC* and *BIC* sometimes select different specifications. In this section we will look at the out-of-sample forecasting performance of the seven models over three sample periods. To obtain the out-of-sample forecasts, we use the following procedure. First we estimate all seven models using T observations starting from quarter D to quarter $D+T-1$. Second, for each estimated model, we obtain the one, two, three, and four-quarter-ahead out-of-sample forecasts for quarters $D+T$, $D+T+1$, $D+T+2$, and $D+T+3$. Third, we add one observation and re-estimate the models using all $T+1$ observations from D to $D+T$, and obtain the one, two, three, and four-quarter-ahead out-of-sample forecasts. We repeat this three-step process through the end of the sub-sample period. Thus for each of the seven models, we have a series of one-step-ahead through four-step ahead forecasts. Since we have the actual values of the federal funds rate for all periods, the bias and mean squared prediction errors (MSPE) of the various forecasting models can be calculated for each forecasting horizon. Note the following:

- Forecasts from the Taylor-rule-type models (Models 1 through 5) require $E_t\pi_{t+k}$ and $E_t y_{t+k}$ as inputs. For the first two periods, the data of $E_t y_{t+k}$ are not available (only within-quarter forecasts for output gap are available). As a result, we use $E_{t+k}y_{t+k}$ in place of $E_t y_{t+k}$. This makes the best possible case for the out-of-sample fit of the Taylor-rule-type models because $E_{t+k}y_{t+k}$ gives more precise information than $E_t y_{t+k}$ when forecasting i_{t+k}.[6]
- Unlike the linear models, the multi-step-ahead forecasts from the exponential and logistic models cannot be obtained recursively. We used the bootstrapping method (with 1000 replications for each forecast) discussed in Chapter 7 of Enders (2004) to obtain the multi-step-ahead forecasts from the exponential and the logistic models.
- To check the robustness of the results, we considered different starting dates *D* and initial estimation periods *T* for each period. For example, we also considered 1982:Q4 as the starting date for the second period because some researchers suggest skipping the period 1979:Q3-1982:Q3 when the Fed temporarily switched from targeting the federal funds rate to controlling non-borrowed reserves. Our results are robust to different starting dates *D* and initial estimation periods *T*.

Table 4 reports the forecasting results of the seven models over three sample periods. The initial estimation periods are 1967:Q1-1974:Q2, 1979:Q3-1989:Q1, and 1987:Q4-1995:Q4, respectively. Over 1967:Q1-1979:Q2, the forward-looking rule generates the smallest MSPE at horizons 1, 2, and 3. The four-quarter-ahead forecasts from the forward-looking rule are not available because the data of $E_t\pi_{t+5}$ contain many missing values and thus are not usable for regression until 1989:Q1. The within-quarter model also forecasts quite well. It has the smallest

[6] Of course, one can not really forecast the federal funds rate this way because $E_{t+k}y_{t+k}$ is not available at quarter *t*. However, the aim of our forecasting exercise is to select the most appropriate rule specifications by comparing their forecasting performance, not to examine the usefulness of the Taylor rule as a forecasting tool. For the last period, both $E_t\pi_{t+k}$ and $E_t y_{t+k}$ are not available. So we use the realized values π_{t+k} and y_{t+k} in place of $E_t\pi_{t+k}$ and $E_t y_{t+k}$.

MSPE at horizon 4 and smallest bias at horizon 2. The nonlinear specifications and the backward-looking rule do not forecast well. The univariate models have the smallest bias at horizons 1, 3, and 4. However, they perform poorly in terms of minimizing MSPE, especially at longer horizons: at horizons 3 and 4, the MSPE of the univariate models is far larger than those of the Taylor-rule-type models. The out-of-sample performance seems to confirm that the forward-looking rule could be the best specification before 1979.

The forecasting results after 1979 are quite interesting in that the univariate models outperform the Taylor-rule-type models at every forecasting horizon. Over 1979:Q3 – 1995:Q4, the AR(1,1) model generates the smallest bias and MSPE at every horizon. Among all the Taylor-rule-type models, the logistic model forecasts best: it has the smallest bias and MSPE among all 5 specifications. This confirms the in-sample results that the logistic specification is the most appropriate form of the policy rule over the second period. The exponential model and the forward-looking rule forecasts fairly well. The backward-looking rule performs poorly at longer horizons.

Over 1987:Q4-2005:Q4, the AR(2) model generates the smallest MSPE at every horizon and the smallest bias at horizon 1. The AR(1,1) model has the smallest bias at horizons 2, 3, and 4. Once again, the univariate models outperform the policy rules. Among all the Taylor rule specifications, the forward-looking rule forecasts the best: it has the smallest MSPE at every horizon. The within-quarter model also forecasts fairly well. The two nonlinear rules do not perform well.

Therefore, the out-of-sample performance generally selects the same policy rule specifications as the in-sample performance does: the forward-looking rule and the logistic rule. However, the results that the univariate models forecast better than the policy rule models after 1979 are quite surprising. There are a number of possible explanations for this. As in Clark and

McCracken (2003), the weakness of the out-of-sample results could be due to neglected shifts in Federal Reserve behavior. However, even with a missing variable, it is unlikely that the simple AR models (which leave out all explanatory variables) would beat the linear and nonlinear forms of the Taylor rule. Another set of explanations is purely econometric since Clements and Hendry (1998) and Liu and Enders (2003) show that an overly parsimonious model may yield better forecasts than one consistent with the true data-generating process. Coefficient instability could result if the Fed responded to inflation and the output gap in a non-mechanical way. To further explore the issue of coefficient instability, we performed the Brown, Durbin, and Evans' (1975) CUSUM test for the forward-looking version of the Taylor Rule. Since the test uses recursive regressions, it allows us to plot out the time paths of the estimated coefficients. Panels a, d and g of Figure 1 show the CUSUMS for the pre-Volcker, Volcker-Greenspan and Greenspan periods, respectively. The recursive coefficient estimates of θ_π are shown in Panels b, e and h and the recursive coefficient estimates of θ_y are shown in Panels c, f, and i.[7] As shown in Panel a of Figure 1, the CUSUMS for the per-Volcker period never leave the upper and lower 5% boundary. Hence, we conclude that the coefficients are stable over the entire pre-Volcker period. The values of θ_π and θ_y (along with a $\pm$ 2 standard deviation band) are shown in Panels b and c of the figure. Notice that the recursive coefficient estimates are stable and the confidence band is quite tight. In contrast, the CUSUMS shown in Panel d quickly depart from 90% confidence interval. Although the recursive estimates of θ_π and θ_y shown in Panels e and f are relatively stable, their confidence intervals are relatively large when compared to the pre-Volcker period. Notice that the confidence interval for the output-gap coefficient is nearly symmetric around zero. As shown in Panel g, the CUSUMS for the Greenspan period start to depart from zero near 2001:Q1. The

[7] The recursive estimates of θ_π and θ_y for the pre-Volcker, Volcker-Greenspan, and Greenspan periods begin using the time periods 1967:Q1-1974:Q2, 1979:Q3-1989:Q1, and 1987:Q4-1995:Q4, respectively. These periods correspond to those of the out-of-sample forecasts reported in Table 4.

recursive estimates θ_π and θ_y are highly volatile and the confidence bands are large and generally include zero. The point is that there is far more coefficient instability in the Volcker-Greenspan and Greenspan periods than in the pre-Volcker period. This is consistent with the notion that the Fed used more discretion in Volcker-Greenspan and Greenspan periods than in the earlier period. In fact, Taylor (1993) was careful to make clear that his proposed rule was not to be interpreted as a purely mechanical one. The following excerpt from his paper should be sufficient to make the point:

"While the analysis of these issues can be aided by quantitative methods, it is difficult to formulate them into a precise algebraic formula. Moreover, there will be episodes where monetary policy will need to be adjusted to deal with special factors. For example, the Federal Reserve provided additional reserves to the banking system after the stock-market break of October 19, 1987 and helped to prevent a contraction of liquidity and to restore confidence. The Fed would need more than a simple policy rule as a guide in such cases."

The extent to which the Federal Reserve used discretion during the Volcker-Greenspan and Greenspan periods is likely to manifest itself in coefficient instability and poor out-of-sample forecasts.

5. Conclusion

In this paper we examine the in-sample and the out-of-sample properties of linear and nonlinear Taylor rules using real-time data. We estimate five most popular specifications of the Taylor rule and two univariate models of the federal funds rate using quarterly U.S. data and compare the in-sample fit of each. The standard measures of in-sample fit (*AIC* and *BIC*) suggest that the linear forward-looking rule or the logistic rule over the 1967:Q1 – 1979:Q2 and 1975:Q3 – 1995:Q4 periods. Among the five specification of the Taylor rule during the Greenspan period, the *AIC* selects the exponential model and the *BIC* selects the forward-looking rule. As such, in-sample measures provide evidence of nonlinearity in the Fed's behavior (especially during the 1975:Q3 – 1995:Q4 period). We also find evidence that the Fed followed the Taylor principle before 1979 if we use the best fitting models. Almost all forms of the rule suggest that the Fed followed the Taylor principle during the Volcker-Greenspan period.

Since out-of-sample forecasting performance can be a useful aid in selecting among alternative functional forms, we also compare the out-of-sample forecasting performance of each model. We find that among all the policy rule models, the out-of-sample performance generally selects the same specifications as the in-sample performance does: the linear forward-looking rule and one nonlinear rule. However, when we compare the out-of-sample performance of the policy rules to those of the two univariate models, we find it quite interesting that the univariate models forecast better than the policy rules after 1979 (but not before 1979).

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Table 1: In-Sample Estimates of the Taylor Rule 1967:Q1 – 1979:Q2

Model	α	θ_π	β_y	ρ	ρ_2	*AIC*	*BIC*
1.Backward-looking	3.740* (3.656)	0.604* (3.381)	0.246 (1.520)	0.675* (6.964)	-0.510* (-3.326)	189.475	199.035
2.Forward-looking	2.097 (1.793)	1.355* (4.666)	0.421* (3.279)	0.676* (9.843)	-0.264* (-1.994)	178.207	187.767
3. Within-quarter	3.806* (3.189)	0.824* (3.518)	0.298* (2.342)	0.685* (8.001)	-0.366* (-2.600)	187.867	197.247
	Constant	Inflation	Output	i_{t-1}	i_{t-2}		
4.Logistic[3]	-0.182 (-0.444)	0.430* (6.134)	0.114* (3.939)	1.149* (7.300)	-0.330* (-2.696)	172.739	195.684
	-5.811 (-1.006)	1.192 (1.458)	0.338 (1.740)	0.047 (0.823)	-0.350* (-2.561)		
	γ = 3.763 (1.921)	*c*=10.043* (37.201)					
5.Exponential[3]	-16.421 (-0.651)	0.726 (1.386)	0.173 (1.296)	3.086 (0.840)	0.286 (0.386)	186.353	209.297
	17.467 (0.694)	-0.337 (-0.614)	-0.040 (-0.271)	-2.058 (-0.555)	-0.650 (-0.863)		
	γ = 5.589 (0.818)	*c*=5.893* (38.412)					
6.AR(2)	6.795* (9.063)			1.330* (10.493)	-0.510* (-3.920)	192.313	198.049
	Constant	Δi_{t-1}					
7. AR(1,1)	0.092 (0.387)	0.402* (3.044)				197.690	201.514

Notes:
1. The Taylor-rule-type models are estimated by NLLS.
2. T-statistics (calculated from robust standard errors) are in parentheses. *Significant at the 5% level.
3. For the logistic and exponential models, the first entries under "Constant", "Inflation", "Output", "i_{t-1}", and "i_{t-2}" are $\alpha_0,\ \alpha_1,\ \alpha_2,\ \alpha_3,$ and $\alpha_4,$ respectively. The second entries are $\beta_0,\ \beta_1,\ \beta_2,\ \beta_3,$ and $\beta_4,$ respectively.

Table 2: In-Sample Estimates of the Taylor Rule 1979:Q3 – 1995:Q4

Model	α	θ_{π}	β_y	ρ	ρ_2	*AIC*	*BIC*
1.Backward-looking	2.337 (1.232)	1.421* (3.336)	0.247 (0.626)	0.819* (12.220)	-0.100 (-0.766)	311.179	322.127
2.Forward-looking	1.430 (0.927)	1.709* (4.368)	0.186 (0.673)	0.780* (10.962)	-0.075 (-0.565)	304.932	315.880
3. Within-quarter	1.945 (1.392)	1.639* (4.534)	0.240 (0.878)	0.775* (11.239)	-0.037 (-0.286)	303.196	314.144
	Constant	Inflation	Output	i_{t-1}	i_{t-2}		
4.Logistic[3]	-0.614 (-1.505)	0.445* (2.648)	0.019 (0.537)	0.882* (2.702)	-0.058 (-0.202)	285.853	312.128
	22.328* (2.846)	0.087* (2.254)	1.191 (1.683)	-0.849 (-1.661)	0.608 (1.757)		
	γ=71.114* (12.510)	c=11.956* (20.289)					
5.Exponential[3]	-1.961 (-0.652)	0.836* (2.174)	-0.056 (-1.333)	0.764 (1.600)	0.072 (0.224)	291.853	318.129
	2.436 (0.821)	-0.787 (-1.625)	0.252* (2.361)	0.305 (0.563)	-0.179 (-0.445)		
	γ=0.412 (1.426)	c=9.232* (23.179)					
6.AR(2)	7.449* (3.102)			1.050* (8.399)	-0.119 (-0.951)	314.071	320.639
	Constant	Δi_{t-1}					
7. AR(1,1)	-0.068 (-0.384)	0.084 (0.672)				314.538	318.917

Notes:
1. The Taylor-rule-type models are estimated by NLLS.
2. T-statistics (calculated from robust standard errors) are in parentheses. *Significant at the 5% level.
3. For the logistic and exponential models, the first entries under "Constant", "Inflation", "Output", "i_{t-1}", and "i_{t-2}" are $\alpha_0, \alpha_1, \alpha_2, \alpha_3,$ and $\alpha_4,$ respectively. The second entries are $\beta_0, \beta_1, \beta_2, \beta_3,$ and $\beta_4,$ respectively.

Table 3: In-Sample Estimates of the Taylor Rule 1987:Q4 – 2005:Q4

Model	α	θ_π	β_y	ρ	ρ_2	*AIC*	*BIC*
1.Backward-looking	0.782 (0.661)	1.386* (2.980)	0.329 (1.172)	0.923* (44.019)	-0.714* (-7.640)	157.120	168.572
2.Forward-looking	1.128 (0.773)	1.303* (1.965)	0.267 (0.816)	0.931* (47.814)	-0.711* (-7.386)	155.463	166.847
3. Within-quarter	0.779 (0.595)	1.382* (2.512)	0.346 (1.087)	0.926* (43.976)	-0.695* (-6.764)	161.897	173.349
	Constant	Inflation	Output	i_{t-1}	i_{t-2}		
4.Logistic[2]	-0.131 (-1.242)	0.106* (2.458)	0.041* (3.535)	1.728* (26.477)	-0.744* (-12.135)	161.885	189.205
	-0.050 (-0.128)	0.130 (1.296)	0.008 (0.217)	-0.179 (-1.502)	0.072 (0.634)		
	γ=5.324* (8.030)	*c*=5.761* (18.534)					
5.Exponential[2]	3.677 (1.627)	-0.322* (-2.664)	-0.010 (-0.313)	1.396* (4.175)	-0.963* (-5.070)	152.844	180.164
	-3.820 (-1.710)	0.549* (4.184)	0.036 (0.734)	0.177 (0.449)	0.278 (1.124)		
	γ=2.269 (1.758)	*c*=5.060* (38.076)					
6.AR(2)[3]	4.644 (4.875)			1.675 (19.915)	-0.718 (-8.544)	158.995	165.866
	Constant	Δi_{t-1}					
7. AR(1,1)	-0.029 (-0.212)	0.698 (8.092)				162.652	167.233

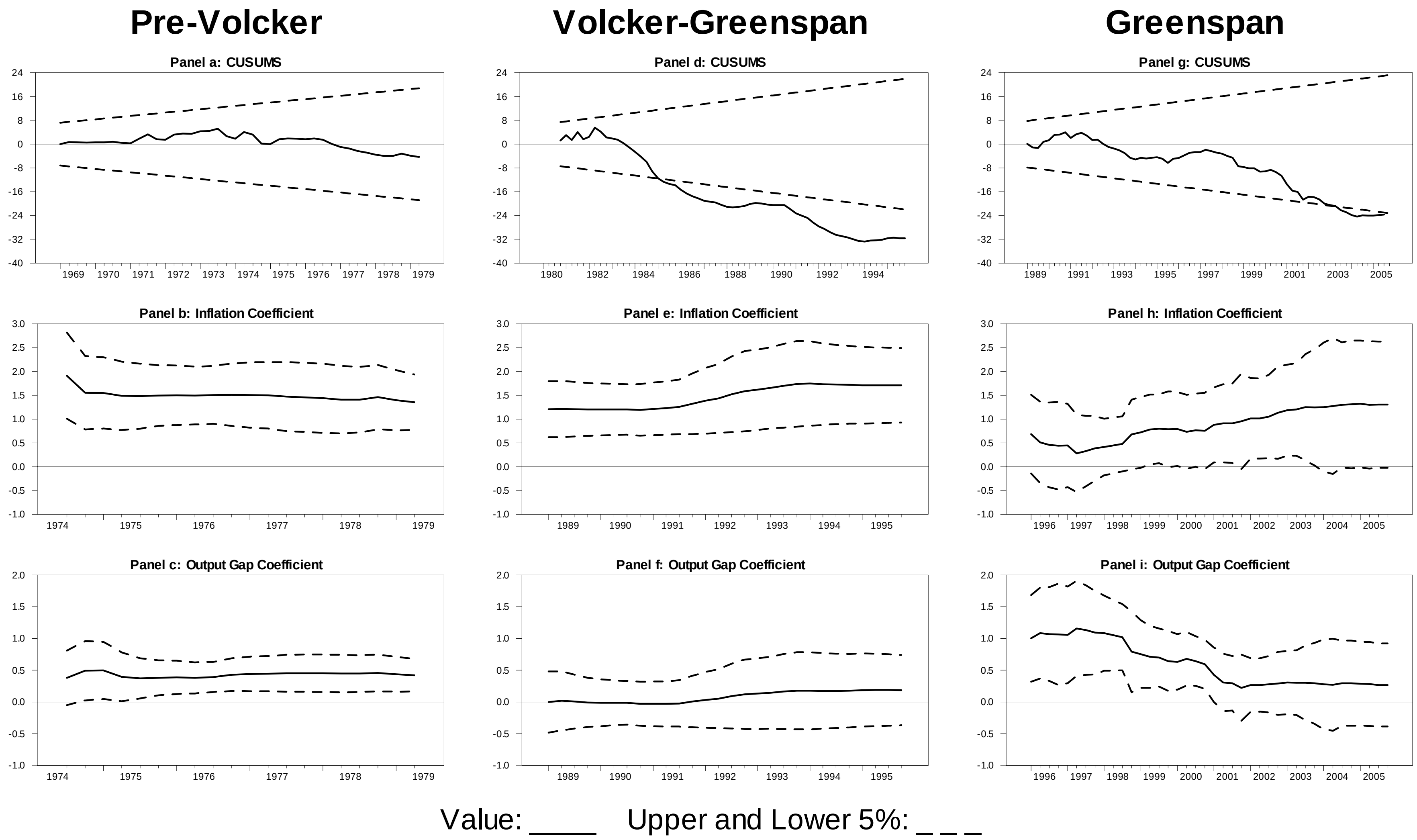
Notes:
1. Models 2,3, 4, and 5 are estimated by GMM.
2. T-statistics (calculated from robust standard errors) are in parentheses. *Significant at the 5% level.
3. For the logistic and exponential models, the first entries under "Constant", "Inflation", "Output", "i_{t-1}", and "i_{t-2}" are α_0, α_1, α_2, α_3, and α_4, respectively. The second entries are β_0, β_1, β_2, β_3, and β_4, respectively.

Table 4: Properties of the Out-of-Sample Forecasts

Model	1–*Step Ahead*		2–*Step Ahead*		3–*Step Ahead*		4–*Step Ahead*	
	Bias	**MSPE**	**Bias**	**MSPE**	**Bias**	**MSPE**	**Bias**	**MSPE**
				The 1967:Q1 – 1979:Q2 Period				
1.Backward-looking	0.184	1.301	0.508	4.228	0.890	4.879	1.260	4.190
2.Forward-looking	-0.214	**0.714**	-0.348	**1.893**	-0.271	**1.758**	N/A	N/A
3.Within-quarter	0.060	0.920	**0.155**	2.566	0.418	2.887	0.745	**2.273**
4.Logistic	-0.377	0.876	-0.783	3.006	-0.941	3.567	-0.996	2.697
5. Exponential	-0.384	0.866	-0.791	2.991	-1.205	3.406	-1.830	4.747
6. AR(2)	**-0.029**	0.829	-0.159	3.159	-0.215	5.147	-0.227	5.304
7. AR(1,1)	-0.098	1.070	-0.218	4.276	**-0.183**	7.522	**-0.072**	9.426
				The 1979:Q3 – 1995:Q4 Period				
1.Backward-looking	-0.422	0.523	-0.926	2.077	-1.357	4.214	-1.724	6.555
2.Forward-looking	-0.454	0.588	-0.904	2.021	-1.229	3.499	-1.502	5.040
3.Within-quarter	-0.550	0.722	-1.051	2.245	-1.427	3.964	-1.703	5.470
4.Logistic	-0.146	0.501	-0.347	1.423	-0.582	2.506	-0.797	3.700
5. Exponential	-0.454	0.569	-0.900	1.904	-1.251	3.345	-1.521	4.624
6. AR(2)	-0.366	0.360	-0.779	1.418	-1.157	2.998	-1.518	5.015
7. AR(1,1)	**-0.055**	**0.221**	**-0.127**	**0.806**	**-0.173**	**1.692**	**-0.217**	**2.912**
				The 1987:Q4 – 2005:Q4 Period				
1.Backward-looking	-0.110	0.176	-0.331	0.816	-0.634	1.900	-0.972	3.175
2.Forward-looking	-0.157	0.137	-0.420	0.645	-0.747	1.584	-1.100	2.829
3.Within-quarter	-0.164	0.143	-0.436	0.668	-0.768	1.616	-1.122	2.846
4.Logistic	-0.180	0.146	-0.491	0.750	-0.909	2.162	-1.372	4.210
5. Exponential	-0.179	0.151	-0.568	1.321	-0.978	3.273	-1.456	5.572
6. AR(2)	**0.011**	**0.106**	0.041	**0.428**	0.081	**1.027**	0.127	**1.868**
7. AR(1,1)	-0.019	0.108	**-0.039**	0.439	**-0.060**	1.056	**-0.080**	1.923

Note:
The initial estimation periods are 1967:Q1-1974:Q2, 1979:Q3-1989:Q1, and 1987:Q4-1995:Q4, respectively.

Figure 1: CUSUMS and Coefficients of the Taylor Rule



Note: The CUSUMS, values of θ_π and θ_y are obtained using the forward-looking Taylor Rule (i.e., Model 2) for each of the three periods.