Stock Return Predictability and Taylor Rules

Onur Ince*
Lei Jiang**
Tanya Molodtsova***

Abstract

This paper evaluates in-sample and out-of-sample stock return predictability with inflation and output gap, the variables that typically enter the Federal Reserve Bank's interest rate setting rule. To examine the role of monetary policy fundamentals for stock return predictability, we introduce inflation and output gap into the Fed model that relates stock returns to earnings and long-term yields. Using real-time data from 1970 to 2008, we find evidence that the in-sample and out-of-sample fit is much stronger for the Fed model with Taylor rule fundamentals than for the constant return model and the original Fed model. In addition to standard MSPE-based out-of-sample comparisons, we use entropy-based tests for nonparametric dependence and find that the performance of the Fed model with Taylor rule fundamentals is more consistent across different window sizes than that of the two alternative models. Finally, we evaluate economic significance of the stock return models and find that the models with Taylor rule fundamentals consistently produce higher utility gains than either the constant return model or the original Fed model. The findings are robust to the choice of the measure of economic activity, data frequency, and window size.

JEL Classification: G10, G11, G14, E44

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* Department of Economics, Walker School of Business, Appalachian State University, Boone, NC, 28608. Tel: +1 (828) 262-4033 Email: inceo@appstate.edu
** Department of Finance, School of Economics and Management, Tsinghua University, Beijing, China, 100084. Tel: +86 (010) 62797084. Email: jianglei@sem.tsinghua.edu.cn
*** Department of Economics, Walker School of Business, Appalachian State University, Boone, NC, 28608. Tel: +1 (828) 262-2117. Email: molodtsovat@appstate.edu

1. Introduction

Despite voluminous literature on stock return predictability, no definite conclusion has yet emerged as to whether stock returns are predictable with any financial and macroeconomic variables. While some studies find evidence of in-sample and/or out-of-sample stock return predictability, the results are not robust to the choice of the sample period and estimation methodology. Those studies that find evidence of stock return predictability with selected variables rarely attempt to explain what drives the relationship. A comprehensive study by Goyal and Welch (2008) summarizes the dismal state of the literature by concluding that none of the conventional macroeconomic or financial variables can predict excess returns in-sample or out-of-sample over the last 30 years.

Studying the links between monetary policy and asset prices is important both for practitioners and policymakers. However, there is a significant disconnection between most empirical research on stock return predictability and the literature on monetary policy evaluation that is based on some variant of the Taylor (1993) rule. The idea that monetary policy decisions affect stock markets is widely accepted among the practitioners. From an investor's point of view, understanding the relationship between stock price behavior and monetary policy is important to gauge empirical asset pricing. Since stock prices are determined in a forward-looking manner, monetary policy is likely to influence stock prices through its influence on market participants' expectations about the future economic activity, which in turn influences the determination of the dividends and stock return premiums. Bernanke and Kuttner (2005) argue that "the most direct and immediate effects of monetary policy actions, such as changes in the federal funds rate, are on the financial markets; by affecting asset prices and returns, policymakers try to modify economic behavior in ways that will help to achieve their ultimate objectives." Thus, exploring the links between monetary policy and asset prices is essential for policymakers to understand the monetary policy transmission mechanism.

An extensive literature has examined the relationship between business condition indicators and changes in stock prices directly. For example, Fama and Schwert (1977) document the negative effect of inflation shocks on the realized common stock returns. Cooper and Priestley (2008) find that the output gap is useful for predicting stock returns. Maio (2013) evaluates economic significance of trading strategies based on the federal funds rate and finds the evidence of significant gains. Boyd et al. (2005) focus on the stock market's response to employment news, and find that stock prices rise when there is bad labor market news during expansions, and fall during contractions. Campbell and Vuolteenaho (2004) try to explain the negative relationship between the inflation and expected stock returns in three potential ways: (1) inflation drives down the real dividend growth, (2) inflation drives up the risk premium, and (3) inflation illusion makes stock market participants fail to see that higher inflation should increase nominal dividend growth.

In general, the connection between monetary policy and stock returns are examined in the literature either in a structural VAR framework or using event study methodology.[1] This paper is different in two ways. First, we focus on the role of monetary policy for stock return predictability. Second, we explicitly introduce variables that determine the target interest rate in a monetary policy rule into the stock return predictive equation, which allows for richer dynamics than solely using the federal funds rate. A typical interest rate setting rule for the Federal Reserve Bank was introduced by Taylor (1993), and it posits that the nominal interest rate responds to the inflation rate, the difference between inflation and its target, the output gap, the equilibrium real interest rate, and (in different variants of Taylor rule) the lagged interest rate and the real exchange rate. This simple rule has become the dominant method for evaluating monetary policy.[2] Following Clarida, Gali, and Gertler (1998), Taylor rules have been estimated for many countries over different time periods.

In this paper, we connect the business condition variables, such as the inflation and output gap, with the stock return via monetary policy channels. In the setup of our model, we follow Asness (2003), who claims that inflation increases both the nominal interest rate and dividend growth, and assumes that the nominal earning growth is unrelated to inflation expectations. We also assume, as in Campbell and Vuolteenaho (2004), that the subjective risk premium of holding stocks over bonds is unrelated to inflation and constant over time. Therefore, the existence of negative relationship between the inflation and expected stock return in our model is consistent with the inflation illusion argument. Brown et al. (2016) examine the cross-sectional relationship between stock returns and inflation and confirms the Modigliani and Cohn (1979) inflation illusion hypothesis. Compared with previous literature that links stock returns and macroeconomic variables, we ask a different question by looking at the effect of Taylor rule fundamentals on the forecasted stock returns. Looking at the coefficients on inflation and output gap, we find that the output gap coefficient is negative throughout the entire sample with a sharp decline around 2000 and 2003. An increase in the U.S. inflation leads to a decrease in forecasted stock returns over the entire sample. The Federal Reserve responds to an increase in inflation by increasing the federal funds rate, which, in turn, increases, earning-to-price ratio. Furthermore, changes in the interest rates cause stock market participants

[1] For example, Patelis (1997), Thorbecke (1997), and Goto and Valkanov (2002) use VAR-based models to study stock return response to changes in either federal funds rates (FFR), inflation, or federal funds futures. Bernanke and Kuttner (2005) study the impact of monetary policy surprises on stock prices, and find that a 25-basis-point cut in the federal funds rate is associated with a one percent increase in broad stock indexes. Crowder (2006) estimates the response of stock returns to innovations in the federal funds rate in a SVAR model that either includes or excludes price index. He finds positive shocks in FFR leads to immediate declines in S&P 500 returns, and increases in price index lead to higher FFR and lower stock returns. Rigobon and Sack (2004) estimate the response of daily stock returns to changes in FFR in a GARCH model. D'Amico and Farka (2003) study the response to changes in federal funds futures on Federal Open Market Committee (FOMC) meeting days. Both papers conclude that monetary tightening leads to declines in equity returns.

[2] Asso, Kahn, and Leeson (2007) examine the history of the Taylor rule and its influence on macroeconomic research and monetary policy evaluation.

to rebalance their portfolios and generate a negative relationship between inflation and expected stock returns.

To our knowledge, this is the first paper to study the role of monetary policy for stock return predictability using Taylor rule fundamentals. Since investors form their expectations about the future monetary policy based on the variables in Taylor rule fundamentals, including the inflation and output gap in the stock return predictive regression allows us to capture expectations of the market participants about the current and future monetary policy that drive the stock prices over and beyond the changes in the actual interest rate. Several papers in recent years connect exchange rates with market expectations using Taylor rules and find that the exchange rate models with Taylor rule fundamentals outperform the naïve no-change model and conventional purchasing power parity, monetary, and interest rate models in out-of-sample comparisons.[3]

We prefer to use real-time data on inflation and real output to examine in-sample and out-of-sample predictability of monthly stock returns from 1970 to 2008. Real-time data, the data available to investors at the time the decisions were made, is crucial to mimic the decision-making process of stock market participants as closely as possible. The starting point of our analysis is the so-called Fed model that has originated in the annals of a Fed report, but is not officially endorsed by the Fed.[4] The model posits that the stock returns are governed by earnings and nominal interest rate. Despite the Fed model's satisfactory in-sample and out-of-sample performance, it does not reflect how the monetary policy is conducted or evaluated. We modify the Fed model by replacing interest rates with Taylor rule fundamentals and call it the Fed model *with Taylor rule fundamentals,* as opposed to *the original* Fed model. If stock prices react mostly to market expectations about future macroeconomic indicators, which are formed based on current Taylor rule fundamentals, embodying current inflation and output gap estimates could improve the forecasting power of the model. It is worth noting that we estimate rather than impose specific Taylor rule coefficients on inflation and output gap in the stock return forecasting equation.

We consider several specifications of the Fed model with Taylor rule fundamentals. In the simplest Taylor rule, the nominal interest rate responds to changes in inflation and output gap. Following Clarida, Gali, and Gertler (1998), it has become common practice to assume partial adjustment of the interest rate to its target within a period. To incorporate gradual adjustment of the federal funds rate to its target, we include lagged interest rate into the model together with the inflation rate and output gap. We call the model with Taylor rule fundamentals that includes the lagged interest rate the model *with smoothing*. Also, we

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[3] See, for example, Engel, Mark, and West (2008), Ince (2014), Molodtsova and Papell (2009, 2013), Ince, Molodtsova, and Papell (2016), and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008, 2011).

[4] The term "Fed model" was coined by a Prudential Securities strategist, Ed Yardeni, who plotted a time series for the earnings-price ratio of the S&P500 against the 10-year constant-maturity nominal treasury yield in the Federal Reserve Humphrey Hawkins Report for July 1997.

consider the model *with no smoothing* that excludes the lagged interest rate. The Federal Open Market Committee (FOMC) meets every 6-8 weeks to set the target interest rate, and that target rate is achieved gradually over the next few months. Therefore, short-run forecasting power of stock return models could potentially be improved by including Taylor rule fundamentals that signal about future macroeconomic developments.

First, we begin by examining in-sample performance of the Fed model with Taylor rule fundamentals using standard in-sample measures of fit. The in-sample fit of the Fed model with Taylor rule fundamentals is much stronger than that of the constant return and original Fed models. We then evaluate the out-of-sample performance of the model with Taylor rule fundamentals. In fact, as discussed in Inoue and Kilian (2004), in-sample predictability does not necessarily imply out-of-sample predictability, and vice versa. In addition to the comparison with out-of-sample R-squared, defined as one minus the ratio of the mean squared prediction error (MSPE) from the Fed model with Taylor rule fundamentals to the MSPEs of the alternative models, the constant return and original Fed model, the out-of-sample predictability of stock return models is evaluated using two other test statistics that are based on the MSPE comparison: the Diebold and Mariano (1995) and West (1996) (DMW) test and the Clark and West (2006) (CW) test.

While the DMW test statistic is appropriate for testing equal predictability of two non-nested models, when comparing the MSPE's of two nested models, the use of DMW test with standard normal critical values usually results in very poorly sized tests, with far too few rejections of the null.[5] McCracken (2007) tabulated asymptotical critical values that can be used for 1-step ahead forecast comparisons using the DMW test. However, as suggested in Rogoff and Stavrakeva (2008), we use bootstrapped critical values instead of relying on the critical values tabulated in McCracken (2007).[6] The CW test adjusts the DMW statistic for comparisons of non-nested models. Although the simulations in Clark and West (2006) suggest that the inference made using asymptotically normal critical values results in properly sized tests, tests with bootstrapped critical values have higher power.[7]

Based on the DMW and CW statistics, we find strong evidence of stock return predictability for the Fed model with Taylor rule fundamentals, which is robust to using various measures of economic activity and different window sizes.[8] Also, the Fed model with Taylor rule fundamentals outperforms the original Fed model, when most of the observations in the regression equation fall into the period where the

[5] McCracken (2007) shows that using standard normal critical values for the DMW statistic results in severely undersized tests, with tests of nominal 0.10 size generally having actual size less than 0.02.

[6] Both approaches produce virtually identical results.

[7] We bootstrap the critical values for CW test using the algorithm described in Section 4.

[8] Rogoff and Stavrakeva (2008) point out that the evidence of exchange rate predictability with CW and DMW statistics may not be consistent over different window sizes in rolling estimation scheme. Inoue and Rossi (2011) discuss the robustness of out-of-sample forecasting to the size of the forecast window. We use various window sizes to ensure the robustness of the results.

Fed is generally characterized by a Taylor rule. This result suggests that Taylor rule fundamentals contain important predictive information for stock returns that cannot be obtained from interest rates alone.

In addition to the out-of-sample tests that are based on the mean squared prediction error comparison, we use the Bhattacharya-Matusita-Hellinger metric entropy developed by Bhattacharya (1943), Matusita (1955), and Hellinger (1909) to test for the generic dependence of stock returns on Taylor rule fundamentals. The entropy measure is defined over densities of stock returns that are estimated non-parametrically following Maasoumi and Racine (2002). If the actual returns and the returns predicted by the Fed Model with Taylor rule fundamentals are independent, the value of this metric is zero, and it will increase as the model's predictive ability improves. Significant test statistic based on the Bhattacharya-Matusita-Hellinger test indicates that the stock returns depend on the predictors in the Taylor rule model. Although we find significant nonparametric dependence with all models, the performance of the model with Taylor rule fundamentals is more robust to the choice of window size than the performance of the constant return and the original Fed model.

Finally, we evaluate the economic significance of the model with Taylor rule fundamentals. To determine whether a trading strategy based on the Fed model with Taylor rule fundamentals can generate higher utility than a strategy based on either the constant return or the original Fed model, we compare the certainty equivalence for these three models following the methodology in Ferreira and Santa-Clara (2010). We find substantial utility gains from timing the market using the Fed model with Taylor rule fundamentals. The models with Taylor rule fundamentals consistently produce higher utility gains than the alternatives. This finding is also robust to the choice of the measure of economic activity and data frequency.

The rest of the paper is organized as follows. Section 2 introduces the Fed Model with Taylor rule fundamentals that is estimated in-sample and used for out-of-sample model comparisons. In Section 3, we describe the data. Section 4 introduces the out-of-sample methodology and describes how the inference is made. In Section 5, we discuss the empirical results of in-sample and out-of-sample tests. Section 6 concludes.

2. Stock Return Models

The starting point for our analysis is a simple model that became known as the Fed model, where stocks and bonds are competing for space in a representative investor's portfolio. Following the adjustments made for the subjective risk premium of holding stocks versus bonds and the growth rate of the dividends, the earnings to price ratio of a representative stock, or stock market index, should rise after an increase in the long-term bond yields. Otherwise, a decline in the earnings to price ratio could lead investors to invest in the bond market. In the equilibrium, the yield on stocks (earnings to price ratio) is correlated with the yield on bonds:

$$E\left(\frac{e_t}{p_t}\right)^* = \alpha + \beta lty_t \tag{1}$$

where lty is the long term yield on a Treasury bond, and $\frac{e_t}{p_t}$ is the earnings to price ratio.

Stock prices could be under- or over-valued and drive the observed earnings to price ratio away from the equilibrium. For instance, Lander, Orphanides and Douvogiannis (1997) shows that an adjustment of a portfolio between stocks and bonds makes the stock prices move so that the difference between the actual and equilibrium earnings to price ratio will be lower (given exogenous earnings). In the absence of the dividends, the change in the stock return will be correlated with the deviation from equilibrium earnings to price ratio. For example, if $\frac{e_t}{p_t} > E(\frac{e_t}{p_t})^*$, a positive deviation indicates that the stock price is undervalued. Thus, investors would have an incentive to hold more stocks, that causes stock prices to rise in the next period and generates positive stock returns, r_{t+1}:

$$r_{t+1} = \alpha_1 + \beta_1\left[\frac{e_t}{p_t} - E\left(\frac{e_t}{p_t}\right)^*\right] + \varepsilon_{t+1} \tag{2}$$

Substituting equation (1) into equation (2), yields

$$r_{t+1} = \theta + \theta_d \frac{e_t}{p_t} + \theta_{lty} lty_t + \varepsilon_{t+1} \tag{3}$$

where $\theta = \alpha_1 - \alpha\beta_1$, $\theta_d = \beta_1$, and $\theta_{lty} = -\beta_1\beta$.

We refer to equation (3) as the *original Fed model* thereafter. This model has been found relatively successful in empirical in-sample and out-of-sample analysis. For example, Thomas and Zhang (2008) suggest using the Fed model in describing rational stock markets and providing insights about stock market valuation.

According to the pure expectation theory in Campbell (1987) and Fama and French (1989), we can replace the long-term bond yield in equation (3) with the sum of the term spread and federal funds rate,

$$r_{t+1} = \theta + \theta_d \frac{e_t}{p_t} + \theta_{lty}(term_t + i_t) + \varepsilon_{t+1} \tag{4}$$

where i_t is federal funds rate, and $term_t$ is the term spread.[9]

[9] Even though there is a possible bond risk premium term on the right-hand side of the equation, it is not possible to measure it accurately. Thus, we assume that the risk premium is absorbed by the error term.

Following Taylor (1993), the monetary policy rule to be followed by the Fed is as follows:

$$i_t^* = \pi_t + \phi(\pi_t - \pi^*) + \gamma y_t + rer^* \tag{5}$$

where i_t^* is the target level of the federal funds rate, π_t is the inflation rate, π^* is inflation target, y_t is the output gap, defined as percent deviation of actual output from its potential level, and rer^* is the equilibrium level of the real interest rate.

We can combine π^* and rer^* in equation (5) into a constant term, $\mu = rer^* - \phi\pi^*$, which leads to the following equation for the target level of short-term nominal interest rate,

$$i_t^* = \mu + \lambda\pi_t + \gamma y_t \tag{6}$$

where $\lambda = 1 + \phi$.

Following Clarida, Gali and Gertler (1998), we allow for the possibility that the interest rate adjusts gradually to achieve its target level,

$$i_t = (1-\rho)i_t^* + \rho i_{t-1} + v_t \tag{7}$$

where $0 \le \rho < 1$. Substituting equation (6) into (7), yields,

$$i_t = (1-\rho)(\mu + \lambda\pi_t + \gamma y_t) + \rho i_{t-1} + v_t \tag{8}$$

To derive the Fed model with Taylor rule fundamentals that is used for forecasting stock returns, we substitute equation (8) into equation (4),

$$r_{t+1} = \omega + \omega_d \frac{e_t}{p_t} + \omega_t term_t + \omega_\pi \pi_t + \omega_y y_t + \omega_i i_{t-1} + \eta_{t+1} \tag{9}$$

where $\omega = \alpha_1 - \alpha\beta_1$, $\omega_d = \beta_1$, $\omega_t = -\beta_1\beta$, $\omega_\pi = -\beta_1\beta(1-\rho)\lambda$, $\omega_y = -\beta_1\beta(1-\rho)\gamma$, and $\omega_i = -\beta_1\beta\rho$.

If the interest rate adjusts to its target level within a period, $\omega_i = 0$, and the Fed model with Taylor rule fundamentals without smoothing becomes,

$$r_{t+1} = \omega + \omega_d \frac{e_t}{p_t} + \omega_t term + \omega_\pi \pi_t + \omega_y y_t + \eta_{t+1} \tag{10}$$

An increase in the inflation rate and/or output gap would cause the Federal Reserve to increase the federal funds rate to stabilize the economy. Also, an increase in the federal funds rate pushes the implicit equilibrium yield in the stock market up and generates a deviation between observed and equilibrium yield. In the next period, stock prices are expected to decrease to move the yield back towards the equilibrium, which decreases the expected price change or causes a negative expected return.

3. Data

We use monthly data starting from February 1970, the earliest date for which all the variables used in our analyses are available, until November 2008 for the U.S. The end of the sample period is chosen to correspond with (1) the onset of the financial crisis of 2008-2009 and (2) the approximate start of the period when the federal funds rates were effectively at the zero lower bound. Since the objective of the paper is to assess the role of the conventional monetary policy for stock return predictability, the unconventional monetary policy era of post-2008 period is outside of the scope of this study.

The stock return is continuously compounded return on the S&P500 index including dividends obtained from the Center for Research in Security Prices (CRSP). The long term yield on government bond, end-of-month S&P500 index, and moving sum of 12-month earnings on the S&P 500 index are from Amit Goyal's website.[10] Term spread is the difference between the long term yield and the federal funds rate. Earnings to price ratio is the ratio of earnings to S&P500 index. The federal funds rate is taken from the Federal Reserve Bank of St. Louis (FRED) Database.

The real-time prices and seasonally adjusted industrial production index are from the Philadelphia Fed Real-Time Database for Macroeconomists described in Croushore and Stark (2001). The real-time dataset has standard triangular format with the vintage dates on the horizontal axis and the calendar dates on the vertical. The term vintage is used to denote each date for which we have data as they were observed at the time. The real-time data is constructed from the diagonal elements of the real-time data matrix by pairing vintage dates with the last available observations in each vintage. This type of data is referred to as the *first-release data*, as opposed to the *current-vintage data* that uses all the information in each vintage, so the data is fully updated each period. The advantage of using the first-release data is that it reflects market reaction to news about macroeconomic fundamentals. While the first-release data has been used before to examine foreign exchange rate predictability by Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) and Ince (2014), it has not been explored in the literature on stock return predictability. Even though the first available vintage contains the series that starts in 1948, we use the last available observation in each vintage.

The GDP Deflator is used to measure the overall price level in the U.S. economy. The inflation rate is the annual inflation rate calculated using the log difference of the GDP Deflator (the last available observation in monthly vintages) over the previous 12 months. The index of seasonally adjusted industrial production is used to measure the level of output. The output gap depends on the estimate of potential output, a latent variable that is frequently subject to ex-post revisions. Since there is no consensus about which definition of potential output is used by central banks or the public, we follow Ince and Papell (2013)

[10] http://www.goizueta.emory.edu/faculty/AmitGoyal/

and estimate the output gap as percentage deviations of actual output from a linear time trend, quadratic time trend, Hodrick-Prescott (1997) (HP) trend, and Baxter and King (1999) (BK) trend.[11] To take into account the end-of-sample uncertainty created by the HP and BK filters, which becomes even more severe with real-time data when no future data is available and the focus is on the last available observation in each period, we apply the technique proposed by Watson (2007). We use AR (8) model to forecast and backcast the industrial production growth 12-periods ahead before applying the HP and BK filters. The descriptive statistics for the variables are presented in Table 1.

4. Model Comparisons

4.1 MSPE-Based Out-of-Sample Predictability Tests

The central question in this paper is whether Taylor rules can provide evidence of out-of-sample predictability for stock returns. To evaluate the out-of-sample performance of the models with Taylor rule fundamentals, we use two test statistics that are based on the MSPE comparison: the Diebold and Mariano (1995) and West (1996) (DMW) test and the Clark and West (2006). The two tests are described below.

Following much of the literature on stock return predictability, we first compare the out-of-sample performance of the Fed model with Taylor rule fundamentals in equations (9) and (10) to that of the constant return model, which serves as a standard benchmark model in the literature. In this case, we are interested in comparing the mean square prediction errors from two nested models:

Model 1: $y_t = \delta + \varepsilon_t$

Model 2: $y_t = X_t^{'}\beta + \varepsilon_t$, where $E_{t-1}(\varepsilon_t) = 0$

The simplest statistic that is commonly used in the literature to compare the out-of-sample performance of the two models is the out-of-sample R^2, which is defined as follows,

$$OOS - R^2 = 1 - \frac{MSPE_2}{MSPE_1} \tag{11}$$

where $MSPE_1$ and $MSPE_2$ are the mean squared prediction errors from the constant return model and the Fed model with Taylor rule fundamentals, respectively. Therefore, when the MSPE of the Fed model with Taylor rule fundamentals is smaller than that of the constant return model, the out-of-sample R^2 is positive, which presents evidence in favor of the Fed model with Taylor rule fundamentals.

To formally test the null hypothesis that the two MSPEs are equal against the alternative that the MSPE of Model 2 is smaller than that of Model 1, we use the test introduced by Diebold and Mariano

[11] For HP-filtered output gap, we set the smoothing parameter, λ, equal to 14400 to detrend monthly series.

(1995) and West (1996) that uses the sample MSPEs to construct a t-type statistic, which is assumed to be asymptotically normal. To construct the DMW statistic, let

$$\hat{f}_t = \hat{e}_{1,t}^2 - \hat{e}_{2,t}^2 \qquad \text{and} \qquad \bar{f} = P^{-1} \sum_{t=T-P+1}^{T} \hat{f}_{t+1} = \hat{\sigma}_1^2 - \hat{\sigma}_2^2 \, ,$$

where $\hat{e}_{1,t}$ and $\hat{e}_{2,t}$ are the sample forecast errors from Models 1 and 2, respectively. Then, the DMW test statistic is computed as follows,

$$DMW = \frac{\bar{f}}{\sqrt{P^{-1}\hat{V}}} \, , \qquad \text{where} \qquad \hat{V} = P^{-1} \sum_{t=T-P+1}^{T} (\hat{f}_{t+1} - \bar{f})^2 \tag{12}$$

Suppose we have a sample of *T+1* observations. The last P observations are used for predictions. The first prediction is made for the observation *R+1*, the next for *R+2*, …, and the final for *T+1*. We have *T+1=R+P*, where *R* is the size of rolling window, and P the total number of forecasts. To generate prediction for period *t=R+1*, …, *T*, we use only the information available prior to *t*.

McCracken (2007) shows that application of the DMW statistic with standard normal critical values to nested models results in severely undersized tests, which in our case would lead to far too few rejections of the null hypothesis of no predictability. Clark and West (2006) demonstrate analytically that the asymptotic distributions of sample and population difference between the two MSPEs are not identical, namely the sample difference between the two MSPEs is biased downward from zero under the null. To test for predictability, we construct the adjusted test statistic as described in Clark and West (2006) by adjusting the sample MSPE from the alternative model by the amount of the bias. This adjusted CW test statistic is asymptotically standard normal.

After comparing the Fed model with Taylor rule fundamentals to the constant return model, we assess whether introducing inflation and output gap into the original Fed model in equation (3) helps to improve its out-of-sample predictability. In this case, the original Fed model versus the Fed model with Taylor rule fundamentals, the two models are non-nested, and we can use the DMW test statistics solely. Instead of relying on inferences based on the asymptotic critical values for the DMW test provided in McCracken (2007), we bootstrap the critical values using the procedure suggested by Mark (1995), Kilian (1999) and Rapach and Wohar (2006).

We use rolling estimation scheme to allow for more flexibility in the presence of possible structural breaks or time-varying coefficients. Rogoff and Stavrakeva (2008) point out that the evidence of exchange rate predictability with CW and DMW statistics may not be consistent over different window sizes. Similarly, Inoue and Rossi (2011) question the robustness of out-of-sample forecasts to the choice of the forecast window. To avoid selecting a window size ad-hoc, we report the results using five different rolling window sizes with forecast starting in 1983:M3, 1986:M6, 1989:M9, 1991:M11, and 1994:M8 associated with 156-, 195-, 234-, 260-, and 293-month rolling windows starting from February 1970.[12]

4.2 Entropy-Based Nonparametric Dependence Tests

To ascertain the possibility of nonparametric relationship between stock returns and monetary policy variables, we use Bhattacharya-Matusita-Hellinger (BMH) metric entropy measure of non-parametric dependence. The BMH test is used to evaluate non-parametric dependence between distributions of the actual returns and the predicted returns of the competing models: the constant return model, the original Fed model, and the Fed model with Taylor rule fundamentals. The entropy measure allows for a generic, and possibly nonlinear, dependence of actual stock returns on their predictions that originate from the models. To calculate the BMH metric entropy measure, we estimate the stock return densities non-parametrically following Maasoumi and Racine (2002). If the actual and predicted returns are independent, the BMH metric produces a value that is not significantly different from zero. The value of the test statistic increases as the dependence between actual and forecasted stock returns rises.

The test statistic is calculated using the formula,

$$S_{\rho} = \frac{1}{2}\int_{-\infty}^{\infty}\int \left(f_{r,\hat{r}}^{\frac{1}{2}} - f_{r}^{\frac{1}{2}} f_{\hat{r}}^{\frac{1}{2}} \right)^{2} dr d\hat{r} \tag{13}$$

where $f_{r,\hat{r}}$ is the joint density of stock returns and predicted returns, f_r is the marginal density of stock returns, and $f_{\hat{r}}$ is the marginal density of predicted returns. S_{ρ} is normalized between zero and one. Higher values of S_{ρ} indicate stronger dependence of stock returns on the predictors.

To test for the dependence between two distributions, the entropy measure uses the information about the entire distribution of actual and predicted stock returns rather than focusing on just the first two moments. The null hypothesis is the independence of the two distributions. An insignificant statistic indicates the failure of the model rather than simply the absence of correlation between the two distributions, which means that no significant information about stock return distribution is contained in the predictive equation.

Following Maasoumi and Racine (2002), we use kernel density estimator for the density of marginal and joint distributions of actual and predicted returns. The kernel function is the second order Gaussian kernel. The bandwidth is selected via likelihood cross-validation. To calculate the critical values, we bootstrap the statistic under the null of independence.

First, we perform the test for nonparametric dependence for the Fed model with Taylor rule model. Then, we compare it with results for the original Fed model that includes only long term yield in equation

[12] These first forecast dates correspond exactly to P/R ratios of 2, 1.4, 1, 0.8, and 0.6.

(3) and the constant return model to check whether the Taylor rule fundamentals contain more information about the actual stock returns.

4.3 Economic Significance Tests

To answer the question that the trading strategy based on the Fed model with Taylor rule fundamentals can generate higher utility than the strategies based on the constant return and original Fed models, we follow Ferreira and Santa-Clara (2010) to compare certainty equivalence from the competing models.[13]

Suppose that the utility function of a single period representative investor, $U(W_{t+1})$, is strictly increasing and twice differentiable, and W_{t+1} is the wealth level at time $t+1$. Since $E_t[U(W_{t+1})] = U(CE)$, where CE stands for the certainty equivalence, maximizing the expected utility is equivalent to maximizing the certainty equivalence with strictly increasing utility function,

$$CE = E_t(W_{t+1}) - \frac{\gamma}{2} Var_t(W_{t+1}) \tag{14}$$

which is derived from the Taylor approximation. We assume the initial wealth is 1 and the coefficient of relative risk aversion equals γ.

If investors can invest either in a stock or in a risk-free asset,

$$W_{t+1} = w_t r_{t+1} + (1 - w_t) rf_{t+1} \tag{15}$$

where w_t is the weight of stocks in the portfolio, r_{t+1} is the stock return, and rf_{t+1} is return on a risk-free asset at time $t+1$, which is known at time t. To find the weight in the optimal portfolio for an investor, we maximize the certainty equivalence. The optimal weight, $w_t = \frac{E_t r_{t+1} - rf_{t+1}}{\gamma Var_t(r_{t+1})}$, is empirically estimated by $w_t = \frac{\hat{r}_{t+1} - rf_{t+1}}{\gamma Va\hat{r}(r_{t+1})}$, where $\hat{r}_{t+1}$ is the predicted value of stock return from the constant return model, the original Fed model, or the Fed model with Taylor rule fundamentals, $Va\hat{r}(r_{t+1})$ is the estimated variance of stock return, and the risk-aversion parameter, γ, can take the values of 1, 2, or 3. After the portfolio weight is determined, both the return and certainty equivalence will be estimated for each model.

5. Empirical Results

We evaluate the in-sample and out-of-sample stock return predictability with Taylor rule fundamentals from February 1970 to November 2008. In addition to evaluating the performance of

[13] Maio (2013) evaluates the economic significance of trading strategies based on the federal funds rate and finds the evidence of significant gains.

candidate models with parametric norms, we also estimate the Bhattacharya-Matusita-Hellinger (BMH) metric entropy to test for the generic and non-parametric dependence of stock returns on predictive models. Finally, we evaluate the economic gains from using a trading strategy based on the competing models. The Fed model with Taylor rule fundamentals is estimated with and without the lagged interest rate using four different measures of the output gap. To make sure that the results are robust to the choice of the size of the estimation window, we report the results using five different window sizes with initial forecasts starting in 1983:M3, 1986:M6, 1989:M9, 1991:M11, and 1994:M8.

5.1 In-Sample Estimation Results

Table 2 reports the in-sample OLS estimates for the Fed model with Taylor rule fundamentals with and without the lagged interest rates (smoothing vs. no smoothing). For each model, we use four different measures of the output gap. We report the estimates of coefficients on inflation, output gap, and lagged interest rate.[14] The adjusted R-squared and F-statistics are reported in the last two rows of the table.

The estimates of inflation coefficients are negative and statistically significant at the 1% significance level for all 8 specifications. The output gap coefficients are also negative and significantly different from zero at least at the 5% level for all models except the specifications with quadratic output gap. Thus, as the inflation and/or output gap increase, the forecasted stock returns decrease. Although the coefficients on the lagged federal funds rate are not significant, they are also negative as expected. The F-statistics show that all the specifications of the Fed model with Taylor rule fundamentals are overall significant and explain 2 to 5 percent of the in-sample variation in stock returns based on the adjusted R-squared results.

Table 3 presents the results of adjusted R-squared and the Akaike Information Criteria (AIC) for the candidate models to assess their in-sample fit. The in-sample fit of the Fed model with Taylor rule fundamentals is much stronger than that of the two benchmark models. The adjusted R-squared for both benchmark models is virtually 0. Also, all AICs are lower for the model with Taylor rule fundamentals than for the original Fed and constant return models. Thus, we find evidence that the model with Taylor rule fundamentals outperforms both benchmark models in-sample.[15]

The in-sample analysis also provides evidence for the inflation illusion hypothesis. If there would be no significant relationship between inflation and stock return, this would support the claim in Asness (2003) that inflation increases both nominal interest rate and dividend growth at the same level and the effect of inflation on stock returns should be zero. Campbell and Vuolteenaho (2004) discuss the potential

[14] The estimated coefficients on the term spread and earnings-to-price ratio are consistently insignificant and not reported.

[15] In an unreported table, we estimate the equation (9) and (10) without the term spread. The results provide similar evidence in support of the Taylor rule models.

reasons for the negative relationship between inflation and stock return, and confirm the Modigliani and Cohn's (1979) inflation illusion hypothesis. Modigliani and Cohn (1979) assert that stock market investors fail to adjust their expectations for nominal dividend growth to match the rising long-term discount rate due to higher nominal interest rate, which leads to stock market underpricing during high inflation and to overpricing during low inflation.

Overall, we find strong evidence to support the inflation illusion theorem. As shown in Table 2, inflation is negatively correlated with future stock returns, regardless of which specification and measure of economic activity is used.

5.2 MSPE-Based Out-of-Sample Predictability Tests

Inoue and Kilian (2004) show that strong in-sample performance does not necessarily imply strong out-of-sample performance of the model, and vice versa. Thus, we compare the out-of-sample performance of the Fed model with Taylor rule fundamentals with that of the constant return model and the original Fed model. Unlike most of the previous studies that use revised data on macroeconomic variables, we use real-time data on inflation and output gap that were available to investors when forecasts were made.

Table 4 reports a-month ahead out-of-sample forecasting performance of the Fed model with Taylor rule fundamentals against the constant return model using four different measures of economic activity and five different window sizes. Since these 2 models are nested, we report both the DMW and CW statistics with bootstrapped critical values. Three observations can be made based on the results. First, there is strong evidence of stock return predictability with Taylor-rule based specifications. Second, the evidence of stock return predictability is stronger with Taylor rule fundamentals with no smoothing than with smoothing based on all three statistics, the DMW, CW, and the OOS-R^2. Third, the evidence of predictability with Taylor rule fundamentals with no smoothing are significant at least at the 5% level and robust to the choice of output gap estimates and size of rolling window sizes.

Having established that the Fed model with Taylor rule fundamentals outperforms the naïve constant return benchmark, the question remains about its relative out-of-sample performance with respect to the original Fed model. Since the model including Taylor rule fundamentals was derived from the original Fed model, it is ambiguous whether the Taylor rule fundamentals contain more predictive information about the stock returns. Table 5 presents the results of out-of-sample tests for the null of equal predictability between the models. In this case, the two models are non-nested and the DMW test can be used with standard normal critical values. The augmented Fed model outperforms the original model starting from the second half of 1980s. This period coincides with the Great Moderation, the period of significant decline in macroeconomic volatility (including inflation and output) since the mid-1980s, that the U.S. monetary policy is successfully characterized by a variant of Taylor rule. The model with Taylor rule fundamentals outperforms the original model with at least one measure of the output gap for window sizes with the first forecast dates in September 1989, November 1991, and August 1994. Since most of the empirical evidence is consistent with the hypothesis that the Fed adopted some variant of the Taylor rule starting in the mid-1980s, our findings indicate that Taylor rule fundamentals contain additional predictive information for stock returns.

Panels C-E of Table 5 show that the model with interest rate smoothing performs better than the model without smoothing between 2nd quarter of 1986 and 3rd quarter of 1989, the period with relatively higher macroeconomic volatility than the post-1990 period. This result is reasonable as the main channels of monetary policy transmission, such as interest rates, might be subject to inertia and adjust gradually. Since the beginning of November 1991, the model without smoothing significantly outperforms the original Fed model in all cases. Also, the model without smoothing outperforms the original Fed model in 7 out of 8 cases at least at the 10 percent level.

Finally, we look at the inflation and output gap coefficients in rolling windows to study the effects of Taylor rule fundamentals on forecasted stock returns. Figure 1 shows the dynamics of inflation and output gap coefficients from the Fed model with Taylor Rule fundamentals with quarterly data and no smoothing. To produce the two graphs, we use HP-filtered output gap and estimate rolling regressions with the first forecast starting 1989:Q4. Looking at the coefficients on inflation, we find that an increase in U.S. inflation leads to a decrease in forecasted stock returns over the entire sample. The output gap coefficient is also negative throughout the entire sample with a sharp decline around 2000 and 2003. The coefficients follow similar pattern regardless of how potential output is calculated.[16] Our findings indicate that an increase in inflation and/or output gap causes a forecasted decrease in stock returns.

5.3 Entropy-Based Nonparametric Dependence Tests

To relax the assumption of parametric dependence of stock returns on Taylor rule fundamentals, we use the Bhattacharya-Matusita-Hellinger (BMH) metric entropy is used to test for the generic dependence of stock returns on Taylor rule fundamentals. Table 6 reports the results of the entropy-based dependence tests for the Fed model with Taylor rule fundamentals, and Table 7 contains the results for the two benchmark models. The entropy measure is defined over densities of stock returns that are estimated non-parametrically following Maasoumi and Racine (2002). If the actual returns and the returns predicted by the Fed Model with Taylor rule fundamentals are independent, the value of the BMH statistic is zero. The test statistic increases as the model's predictive ability improves. A significant test statistic indicates that the stock return depends on the predictors in the Taylor rule model.

Across the specifications with and without smoothing, we find evidence of nonparametric dependence between the distribution of actual returns and predicted returns from the Taylor rule based

[16] Although these results are not reported, the plots look very similar when we use other measures of economic activity, or when monthly data is used.

models for all forecast windows with at least one measure of output gap. The strongest evidence of nonparametric dependence is found for the model with smoothing, where the evidence of significant nonparametric dependence is found for all window sizes and output gap measures, except for the case with the BK output gap.

The results for the two benchmark models are less consistent across the choice of window size, where significant dependence is found with both models for 4 out of 5 window sizes. Although significant nonparametric dependence can be found with all three models, the Fed model with Taylor rule fundamentals produces the results that are more consistent across different window sizes.

5.4 Economic Significance Tests

Finally, we evaluate economic significance of the model with Taylor rule fundamentals. To determine whether a trading strategy based on the Fed model with Taylor rule fundamentals can generate higher utility than strategies based on the constant return or the original Fed model, we compare the certainty equivalence estimated based on the three models. Table 8 reports the estimated certainty equivalence in percentages for different models and three different values of the risk aversion parameter. Panels A and B report certainty equivalence for the Fed model with Taylor rule fundamentals with and without smoothing, respectively. Panel C reports certainty equivalence for constant return model and the original Fed model.

Taylor rule based models consistently generate higher certainty equivalence statistics than the constant return model and the original Fed model. One exception from this pattern, when the certainty equivalence statistics from the two models are equal, occurs at the highest degree of risk aversion. Thus, there is a strong evidence of important utility gains from timing the market using the Fed model with Taylor rule fundamentals. The result is robust to the choice of the output gap measures.

6. Conclusions

Voluminous research on stock return predictability has not yet provided a conclusive answer about whether stock returns are predictable and which variables can help to improve the forecasts. Using real-time data from 1970 to 2008, we evaluate in-sample and out-of-sample stock return predictability with Taylor-rule based model. The in-sample fit is much stronger for the Fed model with Taylor rule fundamentals than for the constant return model or for the original Fed model. Since in-sample fit does not necessarily imply that the model can predict stock returns out-of-sample, we use parametric and non-parametric tests to compare the model with Taylor rule fundamentals to the two alternative models.

Based on the DMW and CW tests, we find strong evidence of out-of-sample stock return predictability with the Fed model with Taylor rule fundamentals, which is robust to the use of various measures of economic activity, data frequency, and different window sizes. The evidence of stock return predictability is stronger for the models without smoothing than with smoothing and for the models with monthly data than with quarterly data. The Fed model with Taylor rule fundamentals outperforms the original Fed model when most of the observations in the forecasting regression fall into the period when the U.S. monetary policy is generally characterized by a variant of Taylor rule.

In addition to the out-of-sample predictability tests that are based on the mean squared prediction error comparison, we use the Bhattacharya-Matusita-Hellinger metric entropy to test for nonparametric dependence of stock returns on Taylor rule fundamentals. The strongest evidence of nonparametric dependence is found for the model with model estimated using monthly data. The dependence tests show that the Fed model with Taylor rule fundamentals produces the results that are more consistent across different window sizes than the two alternatives.

Finally, we evaluate the economic significance of the Fed model with Taylor rule fundamentals, to see if a trading strategy based on it can generate higher utility than the strategies based on the constant return or the original Fed model. The results indicate that the models with Taylor rule fundamentals consistently produce higher utility gains than either the constant return model or the original Fed model. This finding is robust to the choice of the measure of economic activity and data frequency.

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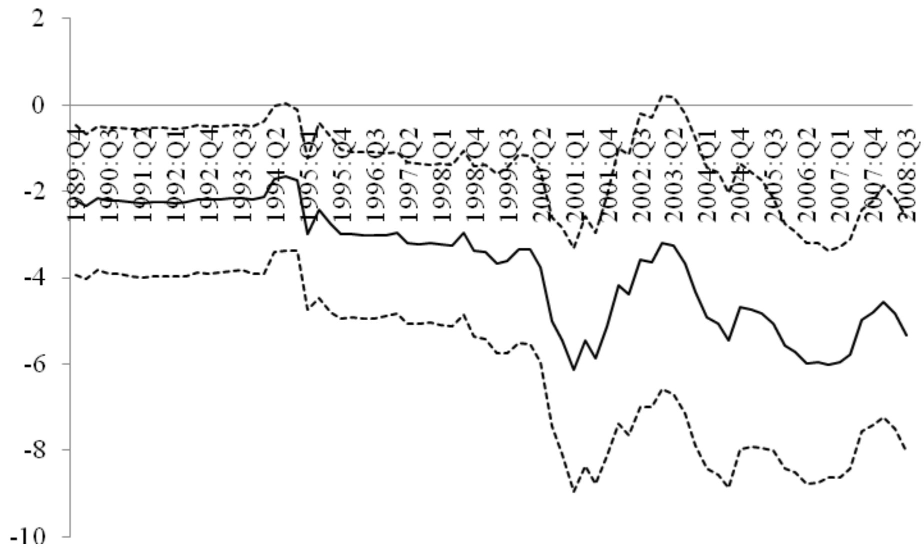
Figure 1. Dynamics of Inflation and Output Gap Coefficients

A. Inflation Coefficient



B. Output Gap Coefficient

Table 1. Descriptive Statistics

	Mean	*Std Dev*	*Min*	*Max*
Stock Return	0.88	4.45	-21.58	16.81
Inflation	3.91	2.40	0.75	11.32
Linear Output Gap	-5.07	3.43	-15.05	2.58
Quadratic Output Gap	0.08	3.03	-10.42	6.26
HP Output Gap	-0.54	1.31	-5.55	1.71
BK Output Gap	-0.53	1.24	-5.83	1.83
Federal Funds Rate	6.48	3.44	0.97	19.10
Long Term Yield	7.70	2.34	4.29	14.82
Earnings (12 month)	26.08	19.29	5.13	84.95
S&P 500 Index	522.48	473.85	63.54	1549.38
Term Spread	1.23	2.01	-6.97	4.41
Earnings Price Ratio	0.07	0.03	0.02	0.15

Notes: Stock return is continuously compounded return on the S&P 500 index including dividends from February 1970 to November 2008 taken from CRSP. Linear Output Gap is linearly detrended output gap, Quadratic Output Gap is quadratically detrended output gap, HP Output Gap is output gap detrended using Hodrick-Prescott (HP) filter with Watson (2007) adjustment, and BK Output Gap is the output gap calculated using Baxter-King (BK) Filter with Watson (2007) adjustment. Long Term Yield is the long term yield on government bonds. Earnings is the moving sum of 12 month earnings on S&P 500 index. Long term yield, S&P500 Index, and Earnings, are taken from Amit Goyal's website. Term Spread is the difference between the long term yield and federal funds rate. Earnings-to-Price Ratio is the ratio of earnings to S&P500 Index. The data are from February 1970 to November 2008.

Table 2. In-Sample OLS Results for the Fed Model with Taylor Rule Fundamentals

	Linear Gap		*Quadratic Gap*		*HP Filter Gap*		*BK Filter Gap*	
	no smoothing	*with smoothing*	*no smoothing*	*with smoothing*	*no smoothing*	*with smoothing*	*no smoothing*	*with smoothing*
Inflation	-0.40***	-0.40***	-0.57***	-0.58***	-1.03***	-1.09***	-0.99***	-1.04***
	(0.17)	(0.17)	(0.23)	(0.23)	(0.25)	(0.26)	(0.24)	(0.25)
Output Gap	-0.16**	-0.18***	-0.16	-0.16	-0.86***	-0.93***	-0.88***	-0.95***
	(0.07)	(0.07)	(0.11)	(0.11)	(0.24)	(0.25)	(0.24)	(0.25)
Lagged FFR	-	-0.10	-	-0.03	-	-0.13	-	-0.13
		(0.13)		(0.12)		(0.13)		(0.13)
Adj-R^2	0.03	0.03	0.02	0.02	0.05	0.05	0.05	0.05
F-stat	4.69***	3.88***	3.71**	2.98**	6.49***	5.41***	6.61***	5.51***

Notes: The table reports OLS regression results for the Fed model with Taylor rule fundamentals with four measures of economic activity (linear, quadratic, HP, and BK output gaps). We only report the coefficients and standard errors for Taylor rule fundamentals, since the coefficient on the term spread is always insignificantly different from zero. The models with smoothing include the first lag of the federal funds rate. The adjusted-R-squared (Adj-R^2) and F-statistics are reported in the last two rows of each panel. The models are estimated using the data from February 1970 to November 2008. Standard errors are reported in parentheses. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 3. In-Sample OLS Results

	AIC	*Adj-R^2*
The Fed Model with Taylor Rule Fundamentals with no smoothing		
Linear Output Gap	2705.15	0.03
Quadratic Output Gap	2708.94	0.02
HP Filtered Output Gap	2698.20	0.05
BK Filtered Output Gap	2697.73	0.05
The Fed Model with Taylor Rule Fundamentals with smoothing		
Linear Output Gap	2706.48	0.03
Quadratic Output Gap	2710.87	0.02
HP Filter Output Gap	2699.09	0.05
BK Filter Output Gap	2698.62	0.05
The Original Fed Model	2715.50	0.00
The Constant Return Model	2715.72	0.00

Notes: The table reports the Akaike Information Criteria (*AIC*) and adjusted- R-squared (*Adj-R^2*) for the two Fed models with Taylor rule fundamentals, the model with no smoothing (Panel A) and the model with smoothing (Panel B), and the two benchmark models (Panel C), the original Fed model and constant return model. The left three columns show the statistics with monthly data, and the right three columns are obtained with quarterly data. The models with Taylor rule fundamentals are estimated using linear output gap, quadratic output gap, Hodrick-Prescott (HP) Filter, and Baxter-King (BK) Filter.

Table 4. A-Month-Ahead Out-of-Sample Forecasts:

The Fed Model with Taylor Rule Fundamentals vs. Constant Return Model

	no smoothing			*with smoothing*		
	DMW	CW	OOS R^2	DMW	CW	OOS R^2
A. First Forecast Date: 1983:M3 (P/R = 2.0)						
Linear Gap	0.02^{***}	2.11^{***}	0.00^{***}	-0.46^{**}	1.86^{**}	-0.01^{**}
Quadratic Gap	-0.36^{**}	1.62^{**}	-0.01^{**}	-0.81^{**}	1.29^{*}	-0.03^{*}
HP Output Gap	0.25^{***}	2.34^{**}	0.01^{***}	-0.07^{***}	2.06^{**}	-0.00^{***}
BK Output Gap	0.27^{***}	2.34^{**}	0.01^{***}	-0.12^{**}	2.08^{**}	-0.00^{**}
B. First Forecast Date: 1986:M6 (P/R = 1.4)						
Linear Gap	0.99^{***}	2.80^{***}	0.03^{***}	0.79^{***}	2.80^{***}	0.02^{***}
Quadratic Gap	0.52^{***}	2.24^{**}	0.01^{***}	0.80^{***}	2.51^{***}	0.02^{***}
HP Output Gap	1.25^{***}	2.94^{***}	0.03^{***}	1.18^{***}	2.96^{***}	0.04^{***}
BK Output Gap	1.30^{***}	3.06^{***}	0.03^{***}	1.23^{***}	3.12^{***}	0.04^{***}
C. First Forecast Date: 1989:M9 (P/R = 1.0)						
Linear Gap	1.51^{***}	3.27^{***}	0.05^{***}	1.56^{***}	3.57^{***}	0.05^{***}
Quadratic Gap	1.25^{***}	2.69^{***}	0.03^{***}	1.57^{***}	3.27^{***}	0.04^{***}
HP Output Gap	1.91^{***}	3.38^{***}	0.05^{***}	1.79^{***}	3.57^{***}	0.05^{***}
BK Output Gap	1.77^{***}	3.31^{***}	0.05^{***}	1.58^{***}	3.52^{***}	0.05^{***}
D. First Forecast Date: 1991:M11 (P/R = 0.8)						
Linear Gap	1.67^{***}	3.03^{***}	0.05^{***}	1.17^{***}	2.85^{***}	0.04^{***}
Quadratic Gap	0.92^{***}	1.99^{**}	0.02^{***}	0.08^{*}	1.87^{**}	0.00^{*}
HP Output Gap	1.32^{***}	2.55^{***}	0.04^{***}	0.99^{***}	2.50^{***}	0.03^{***}
BK Output Gap	1.27^{***}	2.52^{***}	0.04^{***}	0.78^{**}	2.38^{**}	0.03^{**}
E. First Forecast Date: 1994:M8 (P/R = 0.6)						
Linear Gap	1.51^{***}	2.76^{***}	0.06^{***}	1.13^{***}	2.61^{***}	0.04^{***}
Quadratic Gap	0.91^{**}	1.75^{**}	0.02^{**}	-0.20	1.24	-0.00
HP Output Gap	1.32^{***}	2.39^{***}	0.04^{***}	0.84^{**}	2.23^{**}	0.03^{**}
BK Output Gap	1.26^{***}	2.40^{***}	0.04^{***}	0.74^{**}	2.20^{**}	0.03^{**}

Notes: The table reports the DMW and CW statistics for the test for equal predictive accuracy of Taylor rule model and constant return model. R^2 is out-of-sample R-squared. Critical values are obtained using bootstrap with 1000 repetitions. *P/R* includes 2, 1.4, 1, 0.8, and 0.6. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 5: A-Month-Ahead Out-of-Sample Forecasts:

The Fed Model with Taylor Rule Fundamentals vs. the Original Fed Model

	no smoothing		*with smoothing*	
	DMW	OOS R^2	DMW	OOS R^2
A. First Forecast Date: 1983:M3 (P/R=2.0)				
Linear Gap	-0.15	-0.00	-0.75	-0.02
Quadratic Gap	-0.63	-0.02	-1.23	-0.03
HP Output Gap	0.12	0.00	-0.28	-0.01
BK Output Gap	0.14	0.00	-0.34	-0.01
B. First Forecast Date: 1986:M6 (P/R=1.4)				
Linear Gap	0.17	0.00	-0.03	-0.00
Quadratic Gap	-0.44	0.01	-0.17	-0.00
HP Output Gap	0.40	0.01	0.45	0.01
BK Output Gap	0.41	0.01	0.47	0.01
C. First Forecast Date: 1989:M9 (P/R=1.0)				
Linear Gap	1.18	0.04	1.36*	0.04
Quadratic Gap	0.78	0.02	1.50*	0.03
HP Output Gap	1.40*	0.04	1.50*	0.04
BK Output Gap	1.25	0.04	1.28*	0.04
D. First Forecast Date: 1991:M11 (P/R=0.8)				
Linear Gap	1.95**	0.07	1.74**	0.06
Quadratic Gap	1.53*	0.04	0.98	0.02
HP Output Gap	1.79**	0.05	1.68**	0.05
BK Output Gap	1.66**	0.05	1.37*	0.04
E. First Forecast Date: 1994:M8 (P/R=0.6)				
Linear Gap	2.37***	0.09	2.17**	0.07
Quadratic Gap	2.29**	0.05	1.38*	0.03
HP Output Gap	2.36***	0.07	1.94**	0.06
BK Output Gap	2.20**	0.07	1.76**	0.06

Notes: The table reports the DMW statistics for the test for equal predictive accuracy of Taylor rule model and the original Fed model. R^2 is out-of-sample R-squared. DMW critical values are 1.28 at 10%, 1.645 at 5% and 2.325 at 1%. *P/R* includes 2, 1.4, 1, 0.8, and 0.6. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 6. Out-of-Sample Tests for Nonparametric Dependence:

The Fed Model with Taylor Rule Fundamentals

	no smoothing	*with smoothing*
A. First Forecast Date: 1983:M3 (P/R=2.0)		
Linear Gap	0.014***	0.021***
Quadratic Gap	0.012**	0.015***
HP Output Gap	0.010***	0.012**
BK Output Gap	0.011	0.015***
B. First Forecast Date: 1986:M6 (P/R=1.4)		
Linear Gap	0.015	0.019***
Quadratic Gap	0.011	0.013*
HP Output Gap	0.010	0.013**
BK Output Gap	0.010	0.015
C. First Forecast Date: 1989:M9 (P/R=1.0)		
Linear Gap	0.020***	0.024***
Quadratic Gap	0.012	0.014***
HP Output Gap	0.013*	0.023**
BK Output Gap	0.011*	0.012**
D. First Forecast Date: 1991:M11 (P/R=0.8)		
Linear Gap	0.014	0.017*
Quadratic Gap	0.010	0.022***
HP Output Gap	0.011	0.012*
BK Output Gap	0.011	0.011*
E. First Forecast Date: 1994:M8 (P/R=0.6)		
Linear Gap	0.032*	0.027*
Quadratic Gap	0.014	0.019**
HP Output Gap	0.018	0.017*
BK Output Gap	0.010	0.016**

Notes: The table reports the nonparametric metric entropy, S_ρ, for pairwise tests for nonlinear dependence between densities of actual stock returns and predicted values from the model with Taylor rule fundamentals. The critical values are calculated using bootstrap with 100 repetitions. We follow bootstrap methodology in Maasoumi and Racine (2002) and assume that under the null actual returns are independent of predicted returns. *P/R* includes 2, 1.4, 1, 0.8, and 0.6. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 7. Out-of-Sample Tests for Nonparametric Dependence: Benchmark Models

	Constant Return Model	*Original Fed Model*
P/R = 2.0	0.010*	0.018
P/R = 1.4	0.010	0.021***
P/R = 1.0	0.014***	0.017**
P/R = 0.8	0.016***	0.026***
P/R = 0.6	0.014**	0.022***

Notes: The table reports the nonparametric metric entropy, S_ρ, for pairwise tests for nonlinear dependence between densities of actual stock returns and predicted values from the model with Taylor rule fundamentals. The critical values are calculated using bootstrap with 100 repetitions. We follow bootstrap methodology in Maasoumi and Racine (2002) and assume that under the null actual returns are independent of predicted returns. *P/R* includes 2, 1.4, 1, 0.8, and 0.6. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 8. Economic Significance Tests

	γ=1	γ=2	γ=3
A. The Fed Model with Taylor Rule Fundamentals with no Smoothing			
Linear Gap	0.324	0.302	0.288
Quadratic Gap	0.305	0.293	0.283
HP Output Gap	0.315	0.298	0.286
BK Output Gap	0.314	0.297	0.285
B. The Fed Model with Taylor Rule Fundamentals with Smoothing			
Linear Gap	0.329	0.305	0.290
Quadratic Gap	0.307	0.295	0.284
HP Output Gap	0.318	0.299	0.287
BK Output Gap	0.316	0.298	0.286
C. Benchmark Models			
Original Fed Model	0.288	0.284	0.276
Constant Return Model	0.302	0.292	0.283

Notes: This table reports certainty equivalence in percentages for each model at different values of risk aversion factor, γ. Panels A and B report the statistics for the Fed model with Taylor rule fundamentals with and without smoothing using different measures of the output gap. Panel C contains certainty equivalence for the constant return and the original Fed models. P/R ratio is fixed at 0.6, which corresponds to the first forecast data starting in August 1994, or 1994:Q4.