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Monetary Policy Evaluation in Real Time: Forward-Looking Taylor Rules without Forward-Looking Data*

Alex Nikolsko–Rzhevskyy†

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Abstract

There is widespread agreement that monetary policy should be evaluated by using forward-looking Taylor rules estimated with real-time data. For the case of the U.S., this analysis can be performed using Greenbook data, but only through 2002. In countries outside the U.S., central banks do not regularly release their forecasts to the public. I propose a methodology for conducting monetary policy evaluation in real-time when forward-looking real-time data is unavailable. I then implement this methodology and estimate the resultant Taylor rules for the U.S., Canada, the U.K., and Germany. The methodology consists of calibrating models to closely replicate Greenbook forecasts, and then applying them to international real-time datasets. The results show that the U.S. output gap series is well described by quadratic detrending, while Greenbook inflation forecasts can be closely replicated using Bayesian model averaging over Autoregressive Distributed Lag models in inflation and the GDP growth rate. German and U.S. Taylor rules are characterized by inflation coefficients increasing with the forecast horizon and a positive output gap response. The U.K. and Canada interest rate reaction functions achieve maximum inflation response at middle-term horizons of about 1/2 year and the output gap coefficient enters the reaction functions insignificantly. Estimating the U.K. and Canadian Taylor rules as forward-looking is crucial, as backward-looking specifications produce nonsensical estimates. This is not the case for the U.S. and Germany.

JEL Classification: E58, E52, C53
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1 Introduction

During the last decade, simple policy rules have gained increasing popularity as a standard way to monitor and evaluate behavior of central banks. This research was originated by Taylor (1993) who showed that actual monetary policy in the U.S. could be well described by a simple linear function of the inflation rate and a measure of economic activity.

Two important modifications of the original Taylor rule have received wide acceptance. First, Clarida, Gali, and Gertler (1998) departed from the original backward-looking Taylor rule to a forward-looking specification, which arguably better represents the objectives of central banks. In order to control for inflation, the policy instrument would respond to the deviation of the inflation *forecast* from its assumed target.[1] Second, Orphanides (1999, 2000, 2003) stressed the importance of policy rules being *operational* by showing that there are significant differences between monetary policy evaluated over revised data and over real-time data – the data available to policymakers at the time they were making their decisions. This research was further expanded by the work of Croushore and Stark (2001), who collected and made publicly available a real-time dataset for the U.S. It has by now become common practice to evaluate monetary policy for the U.S. based only on real-time data.

For the case of the U.S., real-time forward-looking policy analysis can be performed using the data available in the Greenbook, which contains inflation and output gap forecasts known to the FOMC in real time. The Greenbook, however, is made publicly available with a five year lag, which makes policy analysis after 2002 problematic. In countries outside the U.S., central banks do not regularly release their forecasts to the public and real-time estimates of the output gap are not typically available. The lack of appropriate data is one of the main reasons why research on forward-looking central banks' Taylor rules with real-time data has not been extended past the U.S. to include other countries.

In this paper, I propose a methodology for conducting monetary policy evaluation in real-time when forward-looking real-time data is unavailable. I then implement this methodology and estimate the resultant Taylor rules for the U.S. (including the 2002–2007 period) and three

[1] Approximate and sometimes exact forms of this rule are optimal under the assumption that a central bank has a quadratic loss function over inflation and output deviations from the long run trend (see Svensson (1999) among others).

other countries: Canada, the U.K., and Germany. The methodology consists of four steps. First, I search for a model or a set of models which most closely reconstructs the Greenbook forecasts for the U.S. I evaluate the models based on their ability to replicate the Fed's out-of-sample inflation forecasts and output gap estimates. Second, I apply the best model to construct what U.S. Greenbook projections would have been for the last five years, for which the Greenbook is not yet publicly available, if the Fed had used these models to produce their forecasts. Third, I construct forecasts for the Bank of Canada, Bundesbank, and Bank of England using the same models that produced the best forecasts of inflation and output gap for the U.S.[2] While using existing real-time datasets for the U.S. and Germany, I extend the existing U.K. dataset beyond 2001 and assemble a new real-time dataset for Canada. Finally, after constructing inflation forecasts and output gap estimates, I estimate forward-looking monetary policy reaction functions for all four central banks.

Monetary policy evaluation results show that the U.S. post-2002 monetary policy closely resembles pre-2002 one, where actual Greenbook data is available for estimation. The Taylor rule estimated over the entire sample appears to be forward-looking, characterized with a high inflation response coefficient that increases with the forecast horizon. The output gap coefficient is marginally significant in each specification, and its value is close to Taylor's (1993) postulated value. As we increase the forecast horizon, interest rate smoothing significantly decreases, which indicates that its typical estimate from a "backward-looking" regression might be biased upwards.

German monetary policy reveals strong parallels with U.S. policy. It is characterized by forward-looking behavior, with the inflation coefficient increasing with the forecast horizon, and a positive and significant output gap response. The German output gap coefficient, however, appears to be significantly higher than that of the U.S. Furthermore, evidence shows that the Bundesbank also targeted the USD/DM real exchange rate. Unlike the U.S. and Germany, the U.K. and Canada interest rate reaction functions achieve a maximum inflation response at middle-term forecast horizons of about 1/2 year. Both monetary rules are characterized by small and insignificant output gap coefficients. Estimating Taylor rules for the U.K. and

[2] I do not restrict the coefficients to be the same across countries and, therefore, reestimate the model for Canada, Germany, and the U.K.

Canada as forward-looking is crucial, since backward-looking specifications produce nonsensical estimates. This is not the case for the U.S. and Germany. The forward looking specifications are characterized by a higher than point-for-point inflation response coefficient for each out of four countries, showing that the Fed, the Bank of Canada, the Bundesbank, and the Bank of England obeyed the Taylor principle.

The plan of the remainder of the paper is as follows. In Section 2, I describe the model to be estimated and provide an exposition of a non-linear Taylor rule. In Section 3, I outline the empirical methodology used in my prediction experiment, and describe competing models of inflation and output gap. Section 4 contains a description of the data used, and empirical results are gathered in Section 5. Section 6 concludes.

2 The Model

The original Taylor (1993) monetary policy rule states that a central bank adjusts its short-term nominal interest rate in response to changes in the inflation rate and the output gap. Subsequently, forward-looking policy rules relating the interest rate to expected inflation and the output gap have been found to be more successful than Taylor's original backward-looking specification (Orphanides (2003)). A specification of the Taylor rule that encompasses either contemporaneous or forward-looking policy making would be:

$$i_t^* = E\pi_{t+h} + \delta(E\pi_{t+h} - \pi^*) + \gamma\widehat{y}_t + R^* \quad (1)$$

Here, i^* is the short-term nominal interest rate target, π is the year-over-year inflation rate, π^* is the target level of inflation (usually treated as a constant 2 percent), $\widehat{y}$ is the percentage deviation of output from its long run trend (the output gap), and R^* is the equilibrium level of the real interest rate (also usually 2 percent). Following Clarida, Gali, and Gertler (1998), I assume that the central bank adjusts actual interest rate, i, gradually towards its target level, i^*, as $i_t = (1-\rho)i_t^* + \rho i_{t-1}$, where ρ is the smoothing parameter.

Even for the case of a contemporaneous Taylor rule with $h = 0$, neither right hand side variable of Eq. 1 is observable in real time due to data collecting lags, and therefore expectations of them need to be formed. If we treat π^* and R^* as being constant over time, we can combine them into a single term c and, after allowing for additional policy determinants x_t to affect monetary decisions, the policy rule takes the following form:

$$i_t = \rho i_{t-1} + (1-\rho)\{c + \beta E(\pi_{t+h}|\Omega_t) + \gamma E(\widehat{y}_t|\Omega_t) + \lambda E(x_t|\Omega_t)\} + e_t \tag{2}$$

where $\Omega_t = \{i_t, \pi_{t-1}, \widehat{y}_{t-1}, x_{t-1}, \Omega_{t-1}\}$ is the information set available to policymakers at time t, and x_t might include nominal and real exchange rates, the output gap growth rate, and the foreign interest rate among other possibilities. To obtain an estimatable equation, Clarida, Gali, and Gertler (1998), Gerberding, Worms, and Seitz (2005), and Davradakis and Taylor (2006) eliminate unobserved forecasts from the expression by rewriting Eq. 2 in terms of realized variables, implicitly treating the expectation sign E as being a *rational* expectation of the future. There are three possible problems with this approach. First, realized values of inflation are not available to policymakers in real-time and, therefore, are not part of the information set. Second, using actual future values of inflation creates endogeneity, raising a problem of finding good instruments. Finally, the realized values of inflation is the "effect" of the Fed's policy, not its "cause," and therefore they should not enter the interest rate reaction function in the first place. Indeed, suppose that both output and inflation are close to their target levels, but the Greenbook forecast indicates that, conditional on current policy, we should expect an increase in inflation up to 4% next year, while the policy objective is to keep it close to 2%. Ceteris paribus, this increase in inflation expectations will induce the central bank to intervene and raise interest rates now, which will result in *actual* inflation next year being close to the targeted 2%. If we look at Fig. 1a, we see that after the Fed started targeting inflation in the early 1980s, the Greenbook inflation forecast is typically above realized inflation when the inflation rate is above its target level. This example illustrates a potential source of bias from using realized values of inflation (2%) in the Taylor rule estimation versus the (never actually realized) conditional forecast of 4%, which was in this example the actual driving force for the Fed's actions. Moreover, in the extreme case of perfect monetary control with forward-looking objectives, realized values of inflation would always stay at their target level, and there would be no relationship at all between them and the Central bank interest rate. Therefore, we need to develop a way to construct real-time forecasts.

3 Methods

3.1 Output gap estimation.

In this section I define an appropriate measure of the output gap and develop a way to estimate its value in each period $E(\widehat{y}_t|\Omega_t)$ given the real-time data available to policymakers in various countries. Various measures are judged based on their ability to replicate Greenbook estimates of the output gap.

One way to define the output gap is the difference between actual output and an unobserved trend toward which output tends to revert. Given the limited availability of real-time data for countries outside the United States, I adopt a univariate aggregate approach to estimate the output gap, which requires only real GDP data; this approach is arguably the most common way of measuring potential output (Taylor (1993), Clarida, Gali, and Gertler (1998), Taylor (1999), Molodtsova, Nikolsko-Rzhevskyy, and Papell (2007) and many others use this method).[3]

There seems to be a consensus to use the latest available real-time data vintage to estimate the output gap. Therefore, each output gap series uses exactly one vintage of GDP data, ensuring that all values in the series are defined in the same way. Following the discussion above, I apply six different detrending methods to the U.S. real GDP data:

1. Linear time trend. The (log of) real GDP y_t is regressed on a constant term and a linear time trend: $X = \{1 \;\; t\}$, with coefficients estimated by OLS. The residuals from this regression, scaled by 100, define the output gap, $\widehat{y}_t$.

2. Quadratic time trend. The output gap is defined as deviations from a quadratic time trend, similarly to the previous case, except $X = \{1 \;\; t \;\; t^2\}$. This detrending method is often considered superior to linear detrending because it accounts for the U.S. productivity slowdown in the 1970s. To add further flexibility to the trend and to improve its ability to capture possible structural breaks, I use OLS and two other estimation methods. First, I

[3]The application of an alternative univariate NAIRU approach is limited due to its imprecise estimation. Staiger, Stock and Watson (1997) estimate the 95% confidence interval for the NAIRU to be 3 percentage points wide. Mishkin (2007) describes in detail this and two other approaches: the production function approach and the dynamic stochastic general equilibrium approach (DSGE). While use of the former is limited by the relatively small number of real-time variables available for countries outside the United States, the latter method requires precise knowledge of the structure of the U.S., U.K., German and Canadian economies. These problems make the aggregate approach the only plausible choice.

use the rolling window estimation, where only last n values of GDP (instead of the entire sample) are used for estimation. Second, I use the constant gain version of weighted least squares, where past observations are discounted geometrically.

3. Band-pass filter. The filter isolates fluctuations in the data that persist for 1.5–8 years (6–32 quarters). The filter and its properties are described in detail in Baxter and King (1999). The symmetric nature of the filter creates an end-of-sample problem, which is very relevant with real-time datasets. To cope with this issue I follow Watson (2007) by using the AR(8) growth rate model to extend the log of real GDP series by 100 datapoints in both directions before applying the filter.[4] The gain is twosome: first, it allows me to obtain a numeric value for the output gap at the end of the (initial) sample; second, it allows me to increase substantially the moving average lag length K.[5]

4. Hodrick-Prescott (HP) detrending. The output gap series is derived by minimizing the loss-function $L = \sum_{t=1}^{T} \widehat{y}_t^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]$, where $\widehat{y}_t = y_t - \tau_t$. Following convention, I use $\lambda = 1600$. To account for end-of-sample distortions created by the filter, I use a technique similar to the one described for the band-pass filter, making a backcast and forecast of 12 observations before applying the filter. The same method is used in Clausen and Meier (2005).

5. Unobserved Component (UC) model. The detrending mechanism is based on Clark (1987). The model assumes that y_t can be decomposed into unobserved non-stationary τ_t and stationary c_t, where τ_t is assumed to follow a random walk with drift, and c_t is an invertible ARMA(p, q) process. Additionally, Clark (1987) imposes a restriction of zero correlation between trend and cycle innovations. This setup does not *a priori* impose any smoothness in trend.

6. Beveridge-Nelson decomposition (B-N). This model is identical in the setup to UC model, but it relaxes the assumption of zero correlation between trend and cycle innovations. Instead, the correlation is estimated from the data; it appears to be close to -1, making

[4] Watson uses an AR(6) model to construct 300 forecasts of *monthly* data.

[5] Before applying the filter, I modify the optimal filter weights, a_h, as functions of the weights of the ideal band-pass filter, b_h, as $a_h = b_h + \theta$, where $\theta = (1 - \sum_{h=-K}^{K} b_h)/(2K+1)$. I do this to impose a unity weight constraint at the zero frequency.

the B-N decomposition more theoretically appealing than the UC model. See Morley, Nelson, and Zivot (2003) for details.

I then compare estimates of the output gap series $(\widehat{y}_{t-1}|y_{t-1})$ from these different models based on their ability to replicate the original real-time "Greenbook" estimates of the output gap $(\widehat{y}_{t-1}|\Omega_t)$ used in Orphanides (2003); the series is available for 1969:1–1997:4.

3.2 Inflation forecasting.

My next step is to find a model that produces U.S. inflation forecasts as close as possible to the Greenbook. I utilize modern inflation-forecasting models and techniques, expanding them to estimate not only over the traditional "current-vintage" data, but also over "diagonals" and "first-release" data[6]

The models I consider can be divided into three groups: simple univariate models, bivariate models (usually in inflation and output growth), and atheoretical multivariate models. Whenever possible, I enhance the original estimation techniques by allowing forecast aggregation for two reasons. First, it is becoming recognized that aggregating forecasts over a set of models produces RMSPE smaller then any single model in the set (Garratt, Koop, Mise, and Vahey (2007), Marcellino, Stock, and Watson (2006), Rapach and Strauss (2007), and many others). Second, anecdotal evidence shows that all central banks construct variety of models, each of which produces a unique forecast.[7] The forecasts are then combined (at least implicitly) into one single number, based on subjective probabilities assigned to each model by banks' officials. Generally, I consider both the setup where the weights depend on the in-sample fit of the model and on its out-of-sample performance.[8]

[6]If we define a value of a variable X_t at time k as it is though of in vintage v as x_k^v, then the ith lag of the variable X_t is defined as this sequence of values: $\{x_{1-i}^t, \dots, x_{t-1-i}^t, x_{t-i}^t\}$ for "current vintage," $\{x_{1-i}^{1-i}, \dots, x_{t-1-i}^{t-1-i}, x_{t-i}^{t-i}\}$ for "first releases," and $\{x_{1-i}^1, \dots, x_{t-1-i}^{t-1}, x_{t-i}^t\}$ for "diagonals." See Koenig, Dolmas, and Piger (2003) for details. Table A-1 in Appendix provides an example. Corradi, Fernandez and Swanson (2007) postulate that "current vintage" is arguably the data used by the Federal Reserve and other forecasters.

[7]The famous "Rivers of Blood" chart built by the Bank of England is a good example. See, for example, Wallis (1999).

[8]It is also worth noting is that the U.S. real-time dataset is much larger than the real-time datasets for other countries – typically, U.S. data is available for a longer period and includes more real-time variables. Keeping in mind the ultimate goal of applying the best model to datasets for the United Kingdom, Canada, and Germany (which contain fewer variables), I utilize only a small subset of available real-time variables for the United States. This choice means that the forecasting results I obtain could possibly be improved by expanding the number of variables included, but if I did so the results would not be transferable to other countries.

The models I use are as follows:

1. A random walk (RW) model. This is a standard benchmark model used in most forecasting exercises. If we define π_{t-1} to be the last available observation of inflation at time t, then the RW model makes a no-change forecast of inflation for any horizon h as $\pi_{t+h} = \pi_{t-1} + \varepsilon_t$. Atkeson and Ohanian (2001) compare the RMSPE of Greenbook and random walk forecasts of inflation, and find them very similar. However, Faust and Wright (2007) replicate their study using an extended dataset, and show the superiority of the Greenbook forecast.

2. Iterated autoregression (IAR). Another standard benchmark model is the AR(p) autoregressive model, where inflation π_t is assumed to depend only on its past values: $\pi_t = \rho_0 + \sum_{j=1}^{p} \rho_j \pi_{t-j} + \varepsilon_t$. An h-period forecast is constructed by simply iterating the 1-step ahead forecast. For "diagonals" and "first release" models I set $p = 4$, and for the "current vintage" specification, I fix $p = 8$ since it appears to perform better.[9] The IAR model is also used as a benchmark model in Koenig, Dolmas, and Piger (2003).

3. Direct forecast from autoregression (DAR). This model is closely related to the IAR model above, but in this model, each h-step ahead forecast is a simple 1-step ahead forecast from an appropriate model: $\pi_{t+h} = \rho_0 + \sum_{j=1}^{p} \rho_j \pi_{t-j} + \varepsilon_t$. Asymptotically, the IAR model outperforms the direct AR if the IAR is correctly specified, but the direct forecast may be more robust to possible misspecification (Marcellino, Stock and Watson (2006)). Orphanides and van Norden (2005) find that on average, autoregressive forecasts outperform more complicated output-gap-based forecasts.

4. ARMA(1, 1). This framework models inflation as the sum of expected inflation and noise, which fits the rational expectation framework: $\pi_t = \rho_0 + \rho_1 \pi_{t-1} + \psi_1 \varepsilon_{t-1} + \varepsilon_t$. The empirical motivation for this model comes from Ang, Bekaert, and Wei (2007) who show that ARMA(1, 1) is often the best performing time series model for various measures of inflation. Moreover, for the case of CPI inflation, it outperforms all Phillips curve and

[9] The same set up is used for other autoregressive models described below, unless otherwise noted. Estimation results for uniform $p = 4$ and $p = 8$ are presented in Appendix in Tables A-4 and A-5, respectively. The appendix is available in pdf format for viewing or downloading at www.nikolsko-rzhevskyy.com.

term-structure models. The model is estimated by maximum likelihood, conditioning on the assumption $\varepsilon_1 = 0$. Inflation forecasts for various horizons h are computed recursively.

5. Constant gain CG-VAR(p). This model is similar to the best performing model in Branch and Evans (2006), who use a low order constant gain VAR model in output growth g_t^y and inflation π_t to forecast inflation out of sample. If we define $Y_t = \{\pi_t, g_t^y\}'$, $\epsilon_t = \{\varepsilon_{1t}, \varepsilon_{2t}\}'$, $\mu = \{\mu_1, \mu_2\}$, and Φ as a 2×2 matrix of coefficients, then: $Y_t = \mu + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \epsilon_t$. The model is recursively estimated under various assumptions about the influence of additional observations on parameter estimates. The specification with common constant gain significantly outperforms more complicated alternatives and also provides the best fit with the Survey of Professional Forecasters data.[10] To maximize performance of the model, I consider CG-VAR with 4 different values of gain γ, where $\gamma \in \{0.025, 0.050, 0.075, 0.100\}$.

6. Bayesian Phillips curve. This is the most successful bivariate model used in Orphanides and van Norden (2005) and it enhances the DAR models (above) by adding lags of the real output growth g_t^y not subject to any filtering. Using output growth in this way can be interpreted as implicitly defining an estimated output gap as a one-sided filter of output growth with weights based on the TOFU estimates (van Norden (1995), Orphanides and van Norden (2005)): $\pi_{t+h}^i = \rho_0 + \sum_{j=1}^{p_i^\pi} \rho_j \pi_{t-j} + \sum_{j=1}^{p_i^g} \delta_j g_{t-j}^y + \varepsilon_{it}$. In contrast to Orphanides and van Norden, I do not choose the optimal ADL lag lengths p_i^π and p_i^g based on the Bayesian Information Criterion (BIC). Instead, I estimate m models for every combination of $\{p_i^\pi, p_i^g\} \in \{1..p\}$, and then average the forecasts using the Bayesian model averaging (BMA) approach.[11] Specifically, letting $\widehat{\pi}_{t+h}^i$ be a forecast of π_{t+h} from the ith model, the BMA forecast is $\widehat{\pi}_{t+h} = \sum_{i=1}^{n} \omega_i^t \widehat{\pi}_{t+h}^i$, with ω_i^t being the posterior model probabilities. Asymptotically, it can be shown that the logarithm of the marginal likelihood of a model M_i is proportional to the Schwartz or BIC as $\log P(Data|M_i) \sim \log L - \frac{k \log(T)}{2}$. Under standard noninformative priors about model probabilities, the

[10]Constant gain is a version of weighted least squares, where past observations are discounted geometrically, meaning that each new observation has the same effect on parameter estimates as do past observations. In contrast, traditional OLS employs a "decreasing gain" of t^{-1}, and each new observation has an ever decreasing effect on the parameter estimates.

[11]Garratt, Koop, Mise, and Vahey (2007) show that the best single BIC model never performs as well as a combined forecast. Nocetti and Smith (2006) show that BMA is the *ex ante* optimal way of forecasting in the presence of model uncertainty.

exponent of BIC provides weights proportional to the posterior model probabilities used in BMA, and maximum likelihood estimates (MLEs) can be used as point estimates. Garratt, Koop, Mise, and Vahey (2007) provide additional details. A simplified equal averaging version of this method with $\omega_i = n^{-1}$ is successfully used in Bates and Granger (1969) and Stock and Watson (2003).

7. Model clustering. This technique was first introduced by Aiolfi and Timmermann (2006). The authors split the population of models into K clusters based on models' performance out of sample: Models with the lowest MSPE are assigned to the first cluster, those with slightly worse performance fall in the second cluster, etc. The resulting forecast is the weighted average of individual forecasts of the models from the first cluster. This method works quite well in Rapach and Strauss (2007), who apply it to forecast housing prices. Following them, I also use the $C(K, PB)$ algorithm to average individual forecasts, but I set the number of clusters K equal 5.[12] The battery of models I consider is described as: $\pi^i_{t+h} = \rho_0 + \sum_{j=1}^{p_i^\pi} \rho_j \pi_{t-j} + \sum_{j=1}^{p_i^g} \delta_j g^y_{t-j} + \sum_{j=1}^{J_i} \beta_{ji} x_{jt} + \varepsilon_{it}$. Here, $\{x_{it}\}_{i=1}^n$ is a collection of potential predictors, including the unemployment rate u_t, real output growth g^y_t, and the output gap $\widehat{y}_t$ among others. Lag lengths p_i^π, p_i^g are allowed to vary between $\{1..4\}$, and J_i takes values from $J_j = 0$ (neither x_j variable is included in the model), to $J_j = n$ (all x_j variables are present).[13] Individual forecasts are then combined into one aggregated forecast. The crucial difference between this way of averaging, and the traditional BMA is that with clustering, model weights are assigned based on *out-of-sample* performance of the model, versus the *in-sample* fit with BMA.

8. Data-rich Bayesian model averaging. This model is the large dataset specification that appears to be the only strong competitor to the Greenbook forecast of inflation considered in Faust and Wright (2007): $\pi^i_{t+h} = \rho_0 + \sum_{j=1}^{p} \rho_j \pi_{t-j} + \beta_i x_{it} + \varepsilon_{it}$, where $h = \{0..5\}$ is the forecasting horizon, and $\{x_{it}\}_{i=1}^n$ is a collection of potential predictors. Faust and Wright demonstrate that Bayesian averaging among all n models does a considerably better than

[12] I chose cluster size based on the following procedure. First, I split the sample into 2 parts, and for different values of $K = \{2, 3, 4, 5, 6\}$, I calibrated the model based on its performance over the first part of the sample. Then I tested it using the second part of the sample, and $K = 5$ performed the best.

[13] Thus, this specification embeds a univariate AR(p) model, the bivariate Phillips curve and VAR(p) models, and a number of atheoretical multivariate models.

any of the univariate inflation forecasts, and generally gives the smallest RMSPE among all atheoretical inflation forecasts considered.

4 Real-time Datasets

4.1 U.S. dataset 1965:4–2007:1.

I use two different real-time datasets for the Untied States. The first comes from the Federal Reserve Bank of Philadelphia, and it is described in detail in Croushore and Stark (2001).[14] From the Core Variables/Quarterly Observations/Quarterly Vintages section, I extracted real and nominal GNP/GDP and the unemployment rate, with vintages going back to 1965:Q4. (The last vintage I use is 2007:Q1.) For every variable, the data in each vintage goes back to 1947:1, and new values become available with a one-quarter lag. This means, for example, that for the 2000:Q1 vintage, the last available observation of the real GDP series is for 1999:4. The effective Federal Funds Rate is never revised, and this data comes from the Federal Reserve Board of Governors.[15]

I also use the Greenbook dataset, which is currently available up to 2001:4 (as of October, 2007).[16] From this dataset, I use the annualized quarter-over-quarter growth rate forecast of the GNP/GDP price level, which I transform into year-over-year growth rates by averaging 4 consequent inflation forecasts (some of which are actual realized values).[17] This series and other Taylor Rule variables are plotted at Fig. 1b and Fig. 1c.

4.2 Canadian dataset 1977:3–2007:1.

I assembled the real-time quarterly Canadian dataset using January, April, July, and October issues of the *Bank of Canada Review*,[18] because new updated GDP data is typically released for the first time in these months. The first vintage in the dataset comes from the July 1977 issue

[14]http://www.phil.frb.org/econ/forecast/readow.html

[15]http://www.federalreserve.gov/releases/H15/data/Monthly/H15_FF_O.txt

[16]http://www.philadelphiafed.org/econ/forecast/greenbook-data/index.cfm

[17]For example, inflation at time $t+2$ is the average of these quarter-over-quarter Greenbook entries: a $t+2$ inflation forecast, a $t+1$ inflation forecast, a nowcast of inflation at time t, and the realized inflation at time $t-1$.

[18]Since Winter 1996, the Bank of Canada Review has been published quarterly, and four issues are called Winter, Spring, Summer and Autumn.

of the Review, and the last one is from Spring 2007. The variables included in the dataset are (seasonally adjusted) nominal and real GNP/GDP, money M1/M1Gross (annualized quarter-over-quarter growth rate), the unemployment rate, CPI all items, and Core CPI (over time, the measure changes from CPI All Items minus Food to CPI All Items minus Food and Energy to Core CPI). For real and nominal GDP, data in each vintage goes back to 1960:1. CPI All Items data goes back to 1971:1, while the Core CPI, M1, and unemployment series start in 1972:2. The data is typically updated with a four-month lag, meaning that, for example, in January 1988 the latest real GDP value was for 1987:3. (See Appendix for additional details.)

4.3 German dataset 1979:1–1999:1.

The real-time dataset for Germany was collected by Gerberding, Worms, and Seitz (2005). It consists of real and nominal GDP/GNP, year-over-year CPI inflation, M1/M3 growth rates, the Bundesbank money growth target and internal estimates of the potential output, which makes calculation of the output gap trivial. For real and nominal GDP/GNP, the first available vintage is 1974:Q1, with data going back to 1962:1. CPI vintages start in 1973:4, but typically only 5–8 observations are recorded (the earliest is 1972:4). Finally, money growth vintages begin in 1974:Q1, and the earliest observation is 1970:1. The official money growth targets series was kindly shared by Gerberding, Worms, and Seitz. All variables are typically updated with a one-quarter lag.

4.4 U.K. dataset 1983:3–2007:1

This dataset consists of (seasonally adjusted) real-time real GDP data, downloaded from the Bank of England's online real-time database, described in Egginton, Pick, and Vahey (2002), and GDP deflator data, used in Garratt and Vahey (2006) and Garratt, Koop, Mise, and Vahey (2007), which was kindly shared by the authors. The dataset contains a mixed frequency of vintages for quarterly data; for consistency, I use only those vintages corresponding to the last month in each quarter. The data is consistently available after September 1983, which I use as a starting point in the dataset.[19] The last recorded vintage in this dataset is March 2002, and for

[19] Due to data availability, I had to use July 1992, October 1992 and January 1993 vintages instead of June 1992, September 1992 and December 1992 vintages, respectively, which are missing from the dataset. GDP deflator data contains vintages beginning in November, 1981. There are several reasons why I do not use earlier data.

most major revisions, long time series going back to 1955:1 are recorded. I extended the original dataset to 2007:Q1 using the same source of data (the Office for National Statistics' *Economic Trends*.)

5 Empirics

5.1 Output gap estimation results.

Table 1 compares the in-sample performance of the detrending methods described in Section 3.1. The primary measure of the goodness-of-fit is the Root Mean Square Prediction Error, $RMSPE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \widehat{y}_t)^2}$. Two other measures include the Sign statistics, which shows how often a model matches the Greenbook's booms and recessions, and a simple correlation between the two output gap series. The best performing model in terms of RMSPE is the rolling window detrending, with a window size of 120 quarters (30 years). The strongest correlation among all models is achieved using the constant gain estimation method with $\gamma = 0.005$. In that case, 77% of variation in the Greenbook series is explained by the model. Quadratic detrending is a clear winner among "traditional" detrending mechanisms, with a correlation of 0.87 and a RMSPE of 3.651. Surprisingly, despite its popularity, the Hodrick-Prescott detrending method is one of the worst at predicting the Greenbook estimates: besides having high MRSPE of 5.438, it produces a gap of the same sign as the Greenbook only in slightly more than 50% of cases, and it is virtually uncorrelated with the Greenbook series. The worst performing model is the B-N decomposition, although this result is expected: B-N detrending is known to produce a small and noisy cycle component. The rolling window detrending model with a window size of 80 quarters is among the best models, with a balanced performance in all three categories. In light of these findings, I use the 20 year rolling window as the main method to construct the output gap series for the United States, United Kingdom, and Canada.

First, neither of the monthly real GDP vintages I am interested in is available before September, 1983. Second, the data from the October 1981–July 1982 vintages is missing.

5.2 Inflation forecasting results.

This section details forecasting results of the inflation models, described in Section 3.2. Specifically, I concentrate on the extent to which different models and types of real-time data reproduce conditional (Greenbook) and rational (actual data) forecasts of inflations. The best "Greenbook" model is then used to reconstruct the forecasts for the United States and other countries.

The results, which summarize the relative ability of the forecasting models to replicate Greenbook forecasts, are presented in Table 2. We see that averaging typically gives us the smallest RMSPE (models (6) and (7)), and that the "current vintage" setup produces results superior to both the "diagonals" and "first release" specifications. This result is consistent with the hypothesis that the Fed uses the last available (in real-time) vintage of data to construct its forecasts. Another interesting result is that a simple ARMA(1, 1) model performs exceptionally well for long-term horizons. The "BMA Phillips curve" model (6) with "current vintage" data has the most stable performance among all the models I consider.[20] For the rest of the paper, I use it as my main specification to construct inflation forecasts, as it appears to be the best model to replicate the Greenbook conditional forecasts of U.S. inflation.[21]

For the United States, I combine the original Greenbook inflation forecast (before 2001:4) and my conditional forecast (2002:1–2007:1) into a single series for each forecast horizon h and use it for further estimation.

5.3 U.S. Monetary policy.

5.3.1 History of monetary policy

The inflation stabilization period in the United States started in August 1979 with the appointment of a new Federal Reserve Board Chairman Paul Volcker, who reduced inflation rates in

[20]Anecdotal evidence suggests that the Greenbook contains *conditional* forecasts of the economy at some periods, and *unconditional* at the others, which raises a question of stability of the forecasting model. However, data shows that even if this is indeed the case, the different between the forecasts is minimal. To test this I split the whole sample into two parts, and reestimate all forecasting models for the second part of the Greenbook sample: 1987:2–2000:4. The results are very similar (Appendix, Table A-3), and RMSPE picks the same "current vintage" BMA Phillips curve model as the best model to replicate Greenbook forecasts.

[21]I also investigate whether the model that best predicts the Greenbook forecasts will also be the model that best predicts actual inflation, and I find that the answer is no (Appendix, Table A-12). In fact, using "diagonals" and "first-release" typically produces smaller RMSPE than using "current vintage" data – a finding, similar to Koenig, Dolmas, and Piger (2003)

the U.S. from two-digit numbers in the 1970s to 7% in 1982:1, which I use as a starting point in my estimation sample that runs through 2007:1.

Alan Greenspan replaced Paul Volcker in August 1987, and successfully kept inflation at low levels throughout his chairmanship. Ability to control inflation is typically attributed by researchers to adherence of the Taylor principle, which says that to maintain price stability, a central bank should respond more than one-to-one to deviations of inflation from its target level. Indeed, the Taylor's (1993) original study analyzes Greenspan's 1987:1–1992:3 period and shows that the backward-looking Taylor Rule with an inflation response of 1.5 and an output gap response of 0.5 fits the data remarkably well. Clarida, Gali, and Gertler (1998) estimate a forward-looking Taylor rule over an extended 1979–1994 sample of monthly data, and find the inflation coefficient in a baseline specification to be 1.79. The authors, however, use revised data and realized future values of inflation in place of forecasts, which is subject to my critique.

Orphanides (2004) uses Greenbook forecasts to estimate forward-looking versions of the Taylor rule over a similar time span (1979:3–1995:4) and finds the Fed to be forward-looking: its inflation response appears to be always higher than one, and it increases as the forecast horizon goes from 1 to 4 quarters hence. In his 2003 paper, Orphanides shows that the Taylor rule's fit can be improved if we add a growth targeting term to the baseline Eq. 2 specification. The expected output gap growth $E\triangle\widehat{y}_{t+3} = E\widehat{y}_{t+3} - \widehat{y}_{t-1}$ variable appears to be highly econometrically significant in his 1982:3–1997:4 sample. The value of the expected inflation and expected output gap growth coefficients are 2.73 and 2.68, respectively. Currently, no results are available for 2002:1 and later periods due to the 5-year publication lag for the Greenbook.

I will start by verifying some of the results presented above. Then, I will estimate the forward looking Taylor rule for several subsamples, including one with the last 5 years of data. I fix the sample at 1982:1–2007:1.

5.3.2 Taylor rule estimation (U.S.)

I start with estimating the full sample (1982:1–2007:1) Taylor rule for different forecast horizons $h = \{0..6\}$, where $h = 0$ corresponds to observed $(t-1|t)$ data. The policy variable is the Federal Funds rate at the end of the quarter, giving the Fed time to respond to intra-quarter news. The results are presented in Table 3.[22]

We see that the Fed shows strong pro-active behavior: when the forecast horizon increases, the value of the inflation response coefficient, β, goes up, reaching a maximum of 2.84 (with a standard error of 0.59) at $h = 5$. The goodness of fit measure, R^2, also increases, indicating that the forward-looking version of the Taylor rule fits data better than the backward-looking one. Orphanides (2004) comes to the same conclusion using a 1979:3–1995:4 sample. The output gap coefficient is marginally significant and its value is close to Taylor's (1993) 0.5. Another interesting observation is that the value of the smoothing coefficient $\rho = 0.91$ (with a standard error of 0.05) for $h = 0$ is significantly overestimated compared to $\rho = 0.82$ (with a standard error of 0.05) for $h = 5$. This shows that smoothing does occur, but at a smaller extent than we would conclude in estimating the backward-looking version of the Taylor rule.[23]

My next step is to estimate the forward-looking version of the Taylor rule for two subsamples, one falling on Paul Volcker's chairmanship (1982:1–1987:1) and another on Alan Greenspan and Ben Bernanke's chairmanships (1987:2–2007:1).[24] Besides standard Taylor rule variables (inflation and output gap) I also include the output gap growth variable.[25]

The estimates, which reveal some differences and similarities between the two periods, are presented in Table 4. First, the one-year-ahead inflation forecast response coefficient, β, is statistically identical in both periods, and its size accords to full sample estimates; this result is robust to inclusion of the output gap growth variable. Point estimates, though, are higher in the earlier subperiod. Second, we see that interest rate smoothing increased considerably from 1982–1987 to 1987–2007. Indeed, while $\rho \approx 0.26$ for the former period, it reached 0.86 in the latter one. The difference is also evident in Fig. 1d. Third, the Fed seems to have paid more attention to the output gap after 1987 than it did beforehand: the output gap coefficient is positive and significant for 1987–2007, and insignificant for 1982–1987. Finally, the output gap growth variable is significant in 1987–2007 subsample, but is not significant during Volcker's

[22]To test the validity of inflation forecasts, I compare Taylor rule estimates with both artificial and original Greenbook projections over the Greenbook sample (Table A-6 in Appendix). The difference between them is never econometrically significant. The results also show that using realized values of inflation in place of real-time forecasts might result in biased estimates.

[23]For discussion of other reasons why ρ might be overestimated, refer to Rudebusch (2006) and Lansing (2002).

[24]Note that original Greenbook data is available for the entire 1982:1–1987:1 subsample.

[25]That variable comes from two sources: The Greenbook series before 1997:4 is available in Orphanides (2003). I combine it with the OECD estimates, which could be calculated using the semi-annual issues of OECD *Economic Outlook*. Each issue contains past estimates and future forecasts of annual output gap values for all OECD countries including the US. I obtain quarterly values from annual estimates using quadratic interpolation.

chairmanship. Nevertheless, the Taylor rule specification in each subperiod shows that monetary policy was stabilizing, and the Taylor principle was obeyed.

5.4 Canadian Monetary policy.

5.4.1 History of monetary policy

The estimation sample starts in 1988:1, when the Bank of Canada governor, John Crow, delivered his Hanson Memorial Lecture at the University of Alberta, explicitly setting price stability as the Bank's primary objective, and runs through 2007:1. As Gordon Thiessen, another former Bank of Canada governor, noted in 2000, "The Hanson lecture contained probably the strongest commitment to price stability that had ever come from the Bank of Canada." Following the speech, in February 1991 the Bank of Canada officially announced the introduction of an inflation target. The acceptable range was set at 2–4 percent, with inflation measured by Core CPI (inflation excluding food and energy).[26] Thiessen (2000) defines the current stand of the Canadian monetary policy as "directed towards a single long-run objective: the attainment and maintenance of price stability." During this relatively long history of inflation targeting, inflation rates have declined rapidly, and have stayed roughly within the target range.

Despite significant achievements in controlling inflation, Canada did not experience the stable economic growth and high level of employment that took place in the U.S. In contrast with the "Long Boom" in the United States, Fortin (1996) dubbed the prolonged Canadian recession the "Great Canadian Slump." Curtis (2005) attributes that stagnation to small, statistically insignificant, and sometimes negative policy response to the production gap, compared to similar estimates for the U.S. The author estimates a simple Taylor rule, enhanced with an exchange rate term (the growth rate of the nominal Canadian dollar/U.S. dollar exchange rate) for the period 1987:1–2000:4. He finds the inflation coefficient to be high and comparable to the U.S. coefficient, while the unemployment gap coefficient is significantly lower. The exchange rate coefficient appears to be positive and significant, although all these results are completely reversed for 1995:1–2000:4 sub-sample. The author, however, uses revised data and considers a backward-looking version of the Taylor Rule, while most models used at the Bank of Canada in conducting

[26]Estimation results over 1991:1–2007:1 sample using various measures of the output gap are qualitatively similar to 1998:1–2007:1 results (below), and can be found in Appendix in Table A-7.

monetary policy are forward-looking rules. The Quarterly Projection Model (QPM) – the Bank of Canada's main model for economic projections – typically utilizes inflation-forecast-based (IFB) feedback rules, which include forecasted values of inflation that follow directly from the model. The forecast horizon is typically considered to be 6-7 quarters, with a core inflation rate target of 2% (Cote, Lam, Liu, and St-Amant (2002)). One simple rule developed by Armour, Fung, and Maclean (2002), which is now regularly used in projections, employs high (3.0) response to deviations of inflation from the target and a more standard output gap coefficient (0.5). The parameters of the rules, however, are not estimated but rather calibrated to perform well in the QPM. Therefore, the actual form of the monetary rule used by the Bank of Canada remains an open question.

5.4.2 Taylor rule estimation (Canada)

As with many other central banks, the Bank of Canada uses the Bank Rate to achieve its policy objectives and the target band for the overnight interest rate. Therefore, I use the overnight rate in the middle month of the quarter as a policy variable.[27] The output gap is defined as deviation from a quadratic time trend over the last 20 years, and inflation is measured with the year-over-year growth in the Core CPI. Because the first release of data usually lags by 4 month, the one-quarter-ahead forecast is approximately the "nowcast" of inflation.

I start by estimating the Taylor rule (2) for various forecast horizons h. The results can be seen in Table 3. The first striking result is that when we try to estimate a backward-looking Taylor rule with real-time data, we obtain nonsensical results. Indeed, for $h = 0$, the inflation response, β, is -0.03 and the output gap coefficient, γ, is 1.00 and insignificant. Using contemporaneous data ($h = 1$) does not help: both coefficients stay insignificant, and the Taylor principle appears to be violated. The results change dramatically if we increase the forecast horizon further to $h = 4$ (which corresponds to a 3-quarter-ahead forecast). The inflation coefficient rises to 1.60 and becomes significant, while the output gap coefficient drops to 0.24 but stays insignificant. With an inflation coefficient exceeding 1, my results indicate that the Taylor principle is obeyed. As was the case with the U.S., the smoothing coefficient, ρ, for high values of h is smaller than that for $h = 0$.

[27] As this is the first month after the month to which the real-time dataset refers.

The next step is to check how much, if at all, the inclusion of additional variables affects the estimates (Table 5). As a baseline specification, I choose the forward-looking Taylor rule with $h = 4$. If we omit the interest rate smoothing term, the output gap coefficient becomes negative and significant. This result is the same one obtained by Curtis (2005), which led him to conclude that the negative output gap response might be the main reason of the "Great Canadian slump." However, it we introduce interest rate smoothing, the output gap coefficient becomes positive and statistically insignificant, and this result is stable over several different specifications. In contrast to Curtis' results, the exchange rate coefficient is never econometrically significant, regardless of the presence of interest rate smoothing. The results also show that the Bank of Canada mimicked the behavior of the Fed during this sample period: in specification (3), $\beta = 0.72$, while $\phi = 0.82$. This can be interpreted to mean that 82% of the Bank's monetary policy was following the Fed, while 18% was runing independently with inflation response coefficient $\beta = \frac{0.72}{1-0.82} = 4$.

Finally, I seek to determine whether the Canadian central bank indeed acted to keep inflation inside the target bounds. Econometrically, we cannot separately identify the equilibrium interest rate R^* and the inflation target π^*, but we can get an estimate of π^*, setting R^* equal to the ex-post average real interest rate as $R^* = \frac{1}{T}\sum_{t=1}^{T}(i_t - E\pi_{t+4})$. For our period, $R^* = 2.61\%$, resulting in $\pi^* = 2.88\%$, which is very close to the midpoint of the 2–4 percent target range.

5.5 German Monetary policy.

5.5.1 History of monetary policy

Researchers are generally consistent in identifying a time period for evaluating monetary rules for Germany. As a starting point, researchers typically pick the first quarter of 1979, when the Bundesbank entered the European Monetary System (Clarida, Gali, and Gertler (1998)). The end of the sample falls at the last quarter of 1998, as the Euro was introduced on January 1, 1999. Following a convention, I fix the estimation sample at 1979:1–1998:4.

Using revised data, Clarida, Gali, and Gertler (1998) show that the Bundesbank's monetary policy was proactive and stabilizing, with an inflation coefficient of 1.31 in their baseline specification. The output gap coefficient was also positive and significant, meaning that the Bank responded to real economic fluctuations independently of its concerns about stabilizing inflation.

When the authors allowed U.S. monetary policy to affect the Bundesbank's reaction function through the Federal Funds Rate and the U.S. dollar/Deutche Mark real exchange rate, they found both coefficients to be small but significant. Finally, they tested the conventional view that the Bundesbank simply targeted money growth by including deviations of money growth rates from the target into their regressions. However, they found this variable to be insignificant. Gerberding, Worms, and Seitz (2005) challenge this result by re-estimating the Taylor rule using real-time data, finding money supply to be an important determinant of the Bundesbank's monetary policy. The authors, however, use realized future values of inflation in place of inflation forecasts, which obviously were not available to the central bank's officials at the time they were making decisions. Molodtsova, Nikolsko-Rzhevskyy, and Papell (2007) estimate a completely real-time Taylor Rule for Germany, and they find the money supply coefficient to be small and insignificant. The Taylor Rule specification they consider, though, is backward-looking, so we still lack a reliable real-time, forward-looking estimates of the the Bundesbank's reaction function.

5.5.2 Taylor rule estimation (Germany)

I estimate the Taylor rule using the end-of-quarter Money Market Rate as the policy variable, and year-over-year growth in the GDP deflator as the inflation measure. No detrending of output is needed, since the central bank's real-time estimates of potential output are available.

First, I estimate a forward-looking version of the Taylor rule for various inflation forecast horizons, to check for the presence of proactive behavior in the Bundesbank's monetary policy. The results can be found in Table 3. We see that the inflation response coefficient, β, is always above unity and that its value increases with the forecast horizon, reaching $\beta = 2.40$ for $h = 6$. The output gap coefficient, γ, also increases with the forecast horizon, exceeding 1 for each value of h except $h = 0$. There is mixed evidence of real exchange rate targeting: while the exchange rate coefficient has the correct sign and expected magnitude for short forecast horizons, it becomes increasingly insignificant as h approaches 6 quarters. In contrast with other countries, the value of the smoothing coefficient, ρ, tends to rise as h increases.

My next step is to estimate the forward-looking Taylor rule while allowing for additional variables to enter the interest rate reaction function. The results are shown in Table 5. The

U.S. Federal Funds rate coefficient is small and marginally significant at the 10% level, indicating that the Bundesbank ran a mostly independent monetary policy. Deviation of money growth rate from the target level is not significant in the regression, supporting the findings of Clarida, Gali, and Gertler (1998) and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2007). The real exchange rate only marginally positively enters the Taylor rule at 10% significance level. Its size, however, accords to previous studies. The target inflation rate, π^*, can be estimated similarly to previous cases under the assumption that ex-post $R^* = 3.11\%$. Using estimates from specification (3), this corresponds to $\pi^* = 1.56\%$ (with a standard error of approximately 3%).

5.6 U.K. Monetary policy.

5.6.1 History of monetary policy

I estimation the U.K. Taylor rule over the complete available 1983:3–2007:1 sample, excluding the periods when the Bank of England followed the Bundesbank (1987:1–1990:2) and when the U.K. was a member of the EMS (1990:3–1992:2). During both remaining subperiods, the Bank appeared to target inflation, and both periods had similar price and interest rate dynamics. Indeed, in late 1979, Margaret Thatcher announced the Medium Term Financial Strategy (MTFS), and one of its primary aims was to control inflation. The policy appeared credible, and as a result, inflation fell rapidly, from 19.07% in 1980:1 to 4.98% in 1983:1. And although it spiked again the late 1980s and early 1990s, it never reached the pre-MTFS level (Fig. 2c). Nelson (2003) describes 1979–1987 as a period when "domestic monetary policy emphasized control of inflation, and the exchange rate was largely permitted to float freely." Moreover, "policy makers and advisors did not regard overshoots of the M3 target as intolerable, provided that other measures of monetary conditions [...] were not indicating that monetary policy was loose." In the second half of the 1980s, though, several legislative changes severely complicated the control of the money supply. Therefore, the decision was made to link the value of sterling to the Deutsche Mark; this was done informally from 1987–1990, when monetary policy in the United Kingdom closely followed German policy, and then this fixed exchange rate was formalized through membership in the European Monetary System beginning in October 1990. Due to conflicting external and internal policy objectives and sustained speculative attacks, the United Kingdom left the Exchange Rate Mechanism (ERM) in September 1992, regaining its monetary independence. Clarida, Gali, and Gertler (1998) estimate a simple Taylor Rule regression over a 1979–1990 sample and find that the Bank of England's inflation response coefficient was below unity. When they enhance the Taylor Rule with the Bundesbank's interest rate, they find a statistically significant coefficient of 0.60. The authors interpret this result to mean that the Bank of England followed German monetary policy during this time period, but Nelson (2003) argues that combining the 1979–1987 and 1987–1990 periods into one sample is imprecise due to significant differences between U.K. monetary policies during these regimes: While the Bank of England followed the Bundesbank almost one-for-one during the latter period, it acting independently during the former period.

The post-1992 period is uniformly agreed to be a period of inflation targeting, with a forward-looking Taylor-type rule playing an important role in U.K. monetary policy. According to the 1998 Bank of England Act, the bank's current objectives are to support the government's economic policy with respect to economic growth and unemployment, subject to a price stability commitment (Davradakis and Taylor (2006)). This policy closely resembles the objectives and behavior of monetary authorities during 1979–1987. Indeed, both regimes promoted price stability and successfully restrained inflation, although empirical results for the post-1992 sample are controversial. Davradakis and Taylor (2006) estimate a non-linear Taylor Rule over the 1992–2003 period, finding that the Bank of England's monetary policy can be described as consisting of two regimes: a standard stabilizing Taylor Rule model when inflation exceeds 3.1%, and essentially a RW when inflation is less than or equal to 3.1%. Applying this model to a quarterly real-time dataset would result in just 15 effective observations, which is not enough to obtain credible results. Nelson (2003) estimates the backward-looking Taylor rule for 1992–1997, finding an insignificant coefficient for inflation. The forward-looking specification, though, results in a stabilizing Taylor Rule with coefficients close to the classical 1.5 and 0.5 for inflation and the output gap, respectively.

5.6.2 Taylor rule estimation (U.K.)

Following standard practice, I use the tree month Treasury Bill rate as a proxy for the central bank policy variable, year-over-year growth in the GDP deflator as the inflation measure, and I define the output gap as deviation from a quadratic time trend over the last 20 years. The results of forward-looking Taylor rule estimates are presented in Table 3.[28] The first outcome worth noting is that the backward-looking Taylor rule violates the Taylor principle, with its low (0.95) inflation coefficient. This result concurs with that of Clarida, Gali, and Gertler (1998), who conclude that "the coefficient on the inflation gap is just 0.98." However, if we increase the forecast horizon, the inflation response coefficient increases, reaching a maximum of 1.44 at $h = 3$ quarters, or a 6-month-ahead horizon. The output gap coefficient in this case is 0.22 and insignificant, making both measures very similar to Canadian estimates. As with the United States and Canada, the smoothing coefficient steadily declines with h. The implied target inflation rate, π^*, is estimated to be 4.93%, which corresponds to $R^* = 3.55\%$ and $c = 1.38$.

Next, I question one of the results obtained by Clarida, Gali, and Gertler (1998): that the Bank of England followed the Bundesbank's monetary policy. Clarida, Gali, and Gertler include the German money market rate (MMR) when they estimate the Taylor rule for the 1979–1990 sample, but there is evidence that the 1979–1987 and 1987–1990 subperiods are very different and the Bank of England followed German monetary policy only during the latter period. I estimate their regression over two subsamples with results presented in Table 4. The most important outcome is that indeed, when we (incorrectly) include 1987–1990 subsample in estimation, we conclude that the impact of Bundesbank on the Bank of England was quite significant: about 50% of the U.K. interest rate is determined by the corresponding German interest rate. However, if we exclude 1987–1990 period from our estimation, the MMR response coefficient drops down to essentially zero, with a p-value of 0.995. This suggests that Clarida, Gali, and Gertler's results are driven primarily by this short additional subsample and generally are not valid for other periods. This conclusion is robust to inclusion of the growth in the DM/GBP nominal exchange rate variable.[29]

[28] The results for two extended samples of data, one including 1987:1–1990:2, when the Bank of England was mimicking behavior of the Bundesbank but still excluding 1987:1–1990:2, and another one is the full sample of data from 1983:3 to 2007:1, can be found in Table A-10 in Appendix.

[29] This variable is constructed as a quarterly growth rate of DM/GBP nominal exchange rate before 1999:1, and EUR/GBP after that, with the conversion rate of 1.93DM = 0.69GBP = 1.00EUR.

6 Conclusions

This paper provides an overview of monetary policies in the United States, Canada, Germany, and the United Kingdom over the last 25 years through estimation of forward-looking monetary policy reaction functions when real-time forward-looking data is not available. This issue is extremely important for countries outside the United States, where central banks do not regularly release their forecasts to the public; and for the U.S., because forecasts are released with a five-year lag.

In order to estimate a central bank's real-time interest rate reaction function, it is crucial to develop real-time forecasts of the inflation rate and the output gap when this data is not available. The Greenbook U.S. output gap forecast can be well described by a simple quadratic detrending, while many other popular detrending methods produce results significantly different from the Fed's internal estimates. Greenbook inflation forecasts can be closely replicated using Bayesian model averaging over various lag lengths of the ADL model in inflation and the GDP growth rate. Other aggregate methods also typically produce forecasts superior to single model projections. The paper proceeds to use these forecasts in order to estimate forward-looking Taylor rules in the absence of forward-looking data. The results show that since the 1980s, the Fed, the Bank of Canada, the Bundesbank, and the Bank of England have pursued inflation-targeting monetary policy. However, while the United States and Germany targeted inflation one-year-ahead, the United Kingdom and Canada focused on the middle-term of roughly two quarters hence. Despite these differences, all four central banks obeyed the Taylor principle of having an inflation response coefficient greater than one.

At the present time, the proposed methodology can be applied only to a limited number of countries, for which relatively long real-time datasets are available. Moreover, the methodology considers only a limited amount of information, especially at the inflation forecasting stage, due to a small number of variables recorded. With further development of real-time data, this research can be expanded beyond the U.S., Canada, the U.K., and Germany as real-time datasets for other countries get longer, and the methodology can be significantly improved as the existing datasets become wider.

Aiolfi, M. and Timmermann, A. 2006. Persistence in forecasting performance and conditional combination strategies. *Journal of Econometrics, Elsevier, vol. 127(1-2), pages 31-53*

Ang, A., Bekaert, G., and Wei M., 2007. Do macro variables, asset markets, or surveys forecast inflation better? *Journal of Monetary Economics, Elsevier, vol. 54(4), pages 1163-1212, May*

Atkeson A. and Ohanian, L., 2001. Are Phillips curves useful for forecasting inflation? *Quarterly Review, Federal Reserve Bank of Minneapolis, issue Win, pages 2-11*

Armour J., Fung B., and Maclean, D., 2002. Taylor Rules in the Quarterly Projection Model. *Working Papers 02-1, Bank of Canada*

Aruoba B., 2007. Data revisions are not well-behaved. *Journal of Money, Credit and Banking, forthcoming*

Bates, J.M. and Granger, C.W.J., 1969. The combination of forecasts. *Operations Research Quarterly, 20, pp. 451-468*

Baxter M. and King R., 1999. Measuring Business Cycles: Approximate Band-Pass Filters For Economic Time Series. *The Review of Economics and Statistics, MIT Press, vol. 81(4), pages 575-593, November*

Beffy, P.-O., Ollivaud, P., Richardson, R. and Sédillot, F., 2006. New OECD Methods for Supply-Side and Medium-Term Assessments: A Capital Services Approach. *OECD Economics Department Working Paper no. 482, July 2006.*

Bernanke, B. and Boivin , J., 2003. Monetary policy in a data-rich environment. *Journal of Monetary Economics, 50, pp. 525-546*

Beveridge, S. and Nelson, C., 1981. A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the "business cycle", *Journal of Monetary Economics, Elsevier, vol. 7(2), pages 151-174*

Branch W. and Evans, G., 2005. A simple recursive forecasting model. *Economics Letters, Elsevier, vol. 91(2), pages 158-166, May*

Cayen, J.-P. and van Norden, S., 2005. The reliability of Canadian output-gap estimates. *The North American Journal of Economics and Finance, Elsevier, vol. 16(3), pages 373-393, December*

Clark, P., 1987. The cyclical component of U.S. economic activity. *Quarterly journal of*

Economics 102(4), 1987, pp. 797-814

Clarida, R., Gali, J. and Gertler, M., 1998. Monetary policy rules in practice. Some international evidence. *European Economic Review 42, pp. 1033-1067*

Clausen J. and Meier C.-P., 2005. Did the Bundesbank Follow a Taylor Rule? An Analysis Based on Real-Time Data. *Swiss Journal of Economics and Statistics (SJES), Swiss Society of Economics and Statistics (SSES), vol. 127(II), pages 213-246, June*

Cochrane, J., 1994. Permanent and transitory components of GNP and stock prices. *Quarterly Journal of Economics, vol. 109 (February) pp. 241-265*

Corradi, Valentina, Andres Fernandez and Norman R. Swanson, 2007. Information in the Revision Process of Real-Time Data. *Working paper*

Côté, D., Lam J-P., Liu Y. and St-Amant, P. 2002. The Role of Simple Rules in the Conduct of Canadian Monetary Policy. *Bank of Canada Review, Bank of Canada, vol. 127(Spring), pages 27-35*

Croushore, D., 2007. An evaluation of inflation forecasts from surveys using real-time data. *Working Papers 06-19, Federal Reserve Bank of Philadelphia*

Croushore, D. and Stark, T., 2001. A Real-Time Data Set for Macroeconomists. *Journal of Econometrics, 2001, 105, 111-130*

Curtis, D., 2005. Monetary Policy and Economic Activity in Canada in the 1990s. *Canadian Public Policy, University of Toronto Press, vol. 31(1), pages 59-78, March*

Davradakis, E. and Taylor, M., 2006. Interest rate setting and inflation targeting: evidence of a nonlinear Taylor rule for the United Kingdom. *Studies in Nonlinear Dynamics and Econometrics, Volume 10, issue 4*

Edge, R., Kiley, M. and Laforte, J.-P., 2007. Natural rate measures in an estimated ESGE model of the U.S. economy. *Finance and Economics Discussion Series 2007-8, Washington: Board of Governors of the Federal Reserve System, March*

Egginton, D., Pick, A., and Vahey, S., 2002. 'Keep it real!': a real-time UK macro data set. *Economics Letters, Elsevier, vol. 77(1), pages 15-20, September*

Faust, J., Rogers, J., and Wright, J., 2003. Exchange rate forecasting: the errors we've really made. *Journal of International Economics, Elsevier, vol. 60(1), pages 35-59, May*

Faust, J., Rogers, J., and Wright, J., 2005. News and noise in G7 GDP announcements.

Journal of Money, Credit and Banking, Blackwell Publishing, vol. 37(3), pages 403-19, June

Faust, J. and Wright, J., 2007. Comparing Greenbook and reduced form forecasts using large realtime dataset. *NBER Working Papers 13397, National Bureau of Economic Research, Inc.*

Fernandez, A. and Nikolsko-Rzhevskyy, A., 2007. Measuring the Taylor Rule's Performance. *Economic Letter–Insights from the Federal Reserve Bank of Dallas, Vol. 2, No. 6 June 2007*

Fortin, P., 1996. The Great Canadian Slump. *Canadian Journal of Economics, Canadian Economics Association, vol. 29(4), pages 761-87, November*

Garratt, A., Koop, G., and Vahey, S., 2006. Forecasting Substantial Data Revisions in the Presence of Model Uncertainty. *Birkbeck Working Papers in Economics and Finance 0617, Birkbeck, School of Economics, Mathematics and Statistics.*

Garratt, A., Koop, G., Mise, E. and Vahey, S., 2007. Real-time prediction with UK monetary aggregates in the presence of model uncertainty. *Birkbeck Working Papers in Economics and Finance 0714, Birkbeck, School of Economics, Mathematics and Statistics*

Gerberding, C., Worms, A. and Seitz, F., 2005. How the Bundesbank really conducted monetary policy. *The North American Journal of Economics and Finance Volume 16, Issue 3, December 2005, Pages 277-292*

Hodrick, R. J., and Prescott, E. C., 1997. Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking 29 (1), Feb. 1997, 1-16*

Koenig, E., 2004. Monetary policy prospects. *Economic and Financial Policy Review, Federal Reserve Bank of Dallas, pages 1-16*

Koenig, E., Dolmas, S., and Piger, J., 2003. The Use and Abuse of Real-Time Data in Economic Forecasting. *The Review of Economics and Statistics, MIT Press, vol. 85(3), pages 618-628, 07.*

Kuttner, K.. 1994. Estimating potential output as a latent variable. *Journal of Business and Economic Statistics, vol. 12 (July) pp. 361-368*

Kydland, F. and Prescott, E. 1992. Time to build and aggregate fluctuations. *Econometrica, vol. 50 (November) pp. 361-368*

Lansing, K., 2002. Real-time estimation of trend output and the illusion of interest rate smoothing. *Economic Review, Federal Reserve Bank of San Francisco, pages 17-34*

Mankiw, G. and Shapiro, M., 1986. News or Noise? Analysis of GNP Revisions. *Survey of Current Business, Vol. 66, pp. 20-25, May 1986*

Marcellino, M., Stock, J. and Watson, M., 2006. A comparison of direct and iterated multi-step AR methods for forecasting macroeconomic time series. *Journal of Econometrics, Elsevier, vol. 127(1-2), pages 499-526*

Mishkin, F., 2007. Estimating potential output. *Remarks by Governor Federic S. Mishkin at the Conference on Price Measurement for Monetary Policy, Federal Reserve Bank of Dallas, Dallas, TX, May 24*

Molodtsova, T., Nikolsko-Rzhevskyy, A. and Papell, D., 2007. Taylor Rules and Real-Time Data: A Tale of Two Countries and One Exchange Rate. *Working paper*

Morley, J., Nelson C. and Zivot, E. 2003. Why are Beveridge-Nelson and Unobserved-component decompositions of GDP so Different? *Review of Economics and Statistics, vol. 85 (May 2003), 235-243*

Murray, C., Nikolsko-Rzhevskyy, A. and Papell, D., 2007. Inflation Persistence and the Taylor Principle. *Working paper*

Neiss K. and Nelson, E. 2005. Inflation dynamics, marginal cost, and the output gap: evidence from three countries. *Journal of Money, Credit and Banking, vol. 37 (December) pp. 1019-1045*

Nelson, E. 2003. UK monetary policy 1972–97: a guide using Taylor rules. *Central Banking, Monetary Theory and Practice: Essays in Honour of Charles Goodhart, Volume One. Cheltenham, UK: Edward Elgar, 2003, pp. 195-216*

Nocetti, D., and Smith, W., 2006. Why do pooled forecasts do better than individual forecasts ex post? *Economics Bulletin, Vol. 4, No. 36 pp. 1-7*

Okun, A., 1962, Potential GNP: Its Measurement and Significance. *Proceedings of the Business and Economic Statistics Section, American Statistical Association, Washington, D.C., pp. 98-103*

Orphanides, A., 2001. Monetary Policy Rules Based on Real-Time Data. *American Economic Review, American Economic Association, vol. 91(4), pages 964-985, September*

Orphanides, A., 2003. Historical monetary policy analysis and the Taylor rule. *Journal of Monetary Economics, Elsevier, vol. 50(5), pages 983-1022, July*

Orphanides, A., 2004. Monetary Policy Rules, Macroeconomic Stability, and Inflation: A View from the Trenches. *Journal of Money, Credit and Banking, Blackwell Publishing, vol. 36(2), pages 151-75, April*

Orphanides, A. and van Norden, S., 2005. The reliability of inflation forecasts based on output gap estimates in real time. *Journal of Money, Credit, and Banking - Volume 37, Number 3, June 2005, pp. 583-601*

Rapach D. and Strauss, J. 2007. Forecasting real housing price growth in eight district states. *Federal Reserve Bank of St. Louis Regional Economic Development, forthcoming*

Romer C. and Romer, D. 2000. Federal Reserve Information and the Behavior of Interest Rates. *American Economic Review, American Economic Association, vol. 90(3), pages 429-457, June*

Rudebusch, G., 2006. Monetary Policy Inertia: Fact or Fiction? *International Journal of Central Banking, International Journal of Central Banking, vol. 2(4), December*

Staiger, D., Stock, J. and Watson, M., 1997. The NAIRU, unemployment, and monetary policy. *Journal of Economic Perspectives, vol. 11 (Winter) pp. 33-49*

Svensson, L., 1999. Inflation targeting: some extensions. *Scandinavian Journal of Economics, Blackwell Publishing, vol. 101(3), pages 337-61, September*

Taylor, J., 1993. Discretion versus policy rules in practice. *Carnegie-Rochester Conference on Public Policy 39, pp. 195-214*

Thiessen, G., 2000. Can a bank change? The evolution of monetary policy at the Bank of Canada 1935-2000. *Lecture by Gordon Thiessen, Governor of the Bank of Canada, to the Faculty of Social Science University of Western Ontario, London, Ontario, 17 October 2000*

van Norden, S., 1995. Why is it so hard to measure the current output gap? *Macroeconomics 9506001, EconWPA*

Wallis, K., 1999. Asymmetric density forecasts of inflation and the Bank of Englands fan chart. *National Institute Economic Review, 106112*

Watson M., 2007. How accurate are real-time estimates of output trends and gaps? *Economic Quarterly, Federal Reserve Bank of Richmond, issue Spr, pages 143-161*

Wynne M. and Solomon, G., 2007. Obstacles to measuring global output gaps. *Federal Reserve Bank of Dallas, Economic Letter, Vol. 2, No. 3, March 2007*

Table 1: The relative performance of various detrending methods in reproducing Greenbook 1-quarter-back output gap estimates during 1969:1–1997:4

Model	RMSPE	Sign Test	Correlation
1. Quadratic	3.651	4.45	0.87
2. Linear	4.473	5.19	0.30
3. Rolling window (Quadratic)			
Window = 40	4.645	2.23	0.56
Window = 80	3.320	4.64	0.85
Window = 120	2.837	5.57	0.77
Window = 160	3.759	5.20	0.48
4. Constant gain (Quadratic)			
Gain = 0.005	3.564	5.20	0.88
Gain = 0.010	3.557	5.01	0.87
Gain = 0.015	3.672	5.01	0.84
Gain = 0.020	3.947	4.46	0.80
5. Hodrick-Prescott λ=1600			
Original	5.438	0.19	0.29
Extended by K=12	4.789	2.97	0.56
6. Band pass filter			
Extended by K=12	4.841	2.78	0.54
Extended by K=100	5.084	0.00	0.45
7. Unobserved Component	3.668	5.75	0.60
8. Beveridge-Nelson	5.811	-1.11	-0.06

Notes: All models are estimated over the latest real-time vintage of data ("current vintage"). The window size is expressed in quarters. "Constant gain" discounts past observations geometrically. "Hodrick-Prescott extended" forecasts the (log of) real GDP by K periods into both directions before applying the filter; refer to Baxter and King (1999) for details. "Band pass" filters frequencies between 6 and 32 quarters. The number of MA terms in the filter equals the number of forecasted periods K. The choice of K and the forecasting model accords to Watson (2007). The "Unobserved Component" model corresponds to Clark (1987). The "Beveridge-Nelson" decomposition follows Beveridge and Nelson (1981). The Greenbook output gap data comes from Orphanides (2003). RMSPE stands for "Root Mean Square Prediction Error." The Sign Test is the direction of change test with the null of no predictability.

Table 2: The relative performance of different types of models and real-time data in reproducing Greenbook h-quarter-ahead inflation forecasts during 1974:1–2001:4. Performance is evaluated based on RMSPE

	Univariate				Bivariate		Multivariate	
h-steps	RW	DAR(p)	IAR(p)	ARMA (1,1)	CG-VAR	Phillips Curve	Cluste-ring	Data-rich BMA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Current-vintage								
1	0.395=1.00	0.76*	0.75*	1.02	0.86	0.79	0.76*	0.80
2	0.618=1.00	0.85*	0.85*	1.08	1.12	0.84*	0.85*	0.92
3	0.814=1.00	0.91*	0.91*	0.98	1.28	0.87*	0.91*	0.98
4	0.971=1.00	1.05	1.00	0.97	1.50	0.95*	1.00	1.14
5	1.099=1.00	1.03	0.95	0.89*	1.56	0.84*	0.95	1.10
Panel B. Diagonals								
1	0.395=1.00	1.03	1.02	0.97	1.07	0.89	0.84	0.84
2	0.618=1.00	1.18	1.16	0.95	1.23	1.02	1.03	1.04
3	0.814=1.00	1.32	1.30	0.92	1.35	1.09	1.06	1.12
4	0.971=1.00	1.53	1.46	0.93*	1.44	1.12	1.05	1.15
5	1.099=1.00	1.61	1.48	0.89*	1.45	1.12	1.05	1.25
Panel C. First-release								
1	0.395=1.00	1.06	1.06	0.97	1.07	0.95	0.97	0.98
2	0.618=1.00	1.20	1.24	0.95	1.23	1.05	1.07	1.10
3	0.814=1.00	1.36	1.43	0.92	1.35	1.11	1.09	1.16
4	0.971=1.00	1.58	1.64	0.93*	1.44	1.12	1.06	1.21
5	1.099=1.00	1.70	1.70	0.89*	1.45	1.10	1.04	1.26

Notes: RMSPE stands for "Root Mean Square Prediction Error." Column (1) RW reports the absolute RMSPE; models (2)-(8) report ratio of their RMSPE to that of a RW, with values lower than 1 meaning that a model outperforms the RW. RW stays for random walk no-change forecast. The lag length p is fixed at $p = 8$ for Panel A, and at $p = 4$ for Panels B and C. IAR stays for iterative autoregression. CG-VAR is a constant gain VAR considered in Branch and Evans (2006). Phillips Curve is a variable lag length ADL model in output growth and inflation with the forecast produced using Bayesian model averaging (BMA). Clustering is a Aiolfi and Timmermann (2006) technique with the cluster size K=5. Data-rich BMA comes from Faust and Wright (2007). Refer to Section 3 for further details. A star "*" denotes best performing models at a given forecasting horizon. "Current-vintage," "Diagonals," and "First release" are all types of real-time data, which uses only information available to forecasters at the time they were making forecasts. For explanation of the difference between there three types of data, refer to Table A-1.

Table 3: Real-time forward-looking Taylor rule estimates for different inflation forecast horizons

Variable	Forecast horizon h						
	0	[1]	2	3	4	5	6
	Panel A. U.S. 1982:1–2007:1						
Inflation forecast β	1.56	1.99	2.44	2.58	2.65	2.84	2.72
	(1.18)	(0.79)	(0.64)	(0.71)	(0.67)	(0.59)	(0.62)
Output gap γ	0.40	0.36	0.32	0.31	0.27	0.26	0.30
	(0.36)	(0.27)	(0.22)	(0.21)	(0.20)	(0.18)	(0.19)
Smoothing ρ	0.91	0.88	0.85	0.85	0.84)	0.82	0.83
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.04)
R^2	0.93	0.93	0.94	0.94	0.94	0.94	0.94
	Panel B. Canada. 1988:1–2007:1						
Inflation forecast β	-0.03	0.54	0.91	1.44	1.60	1.50	1.48
	(2.72)	(1.94)	(1.61)	(1.13)	(0.92)	(0.86)	(0.78)
Output gap γ	1.00	0.77	0.60	0.33	0.24	0.21	0.19
	(2.24)	(1.58)	(1.20)	(0.69)	(0.55)	(0.54)	(0.50)
Smoothing ρ	0.97	0.96	0.95	0.93	0.91	0.91	0.91
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)
R^2	0.93	0.93	0.93	0.93	0.93	0.93	0.93
	Panel C. Germany. 1979:1–1998:4						
Inflation forecast β	1.19	1.28	1.25	1.59	1.91	2.17	2.40
	(0.27)	(0.32)	(0.38)	(0.49)	(0.70)	(0.80)	(0.97)
Output gap γ	0.99	1.03	1.14	1.07	1.15	1.17	1.22
	(0.29)	(0.38)	(0.52)	(0.52)	(0.59)	(0.61)	(0.68)
Real exchange rate ξ	0.08	0.08	0.09	0.08	0.08	0.08	0.08
	(0.03)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)	(0.07)
Smoothing ρ	0.80	0.83	0.86	0.87	0.89	0.89	0.90
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
R^2	0.95	0.95	0.95	0.95	0.95	0.95	0.95
	Panel D. U.K. 1983:3–2007:1 except 1987:2–1992:2						
Inflation forecast β	0.95	1.30	1.27	1.44	1.37	1.21	1.12
	(0.86)	(0.75)	(0.55)	(0.39)	(0.30)	(0.26)	(0.25)
Output gap γ	0.46	0.40	0.30	0.22	0.12	0.05	-0.00
	(0.91)	(0.66)	(0.52)	(0.33)	(0.25)	(0.26)	(0.27)
Smoothing ρ	0.91	0.89	0.88	0.84	0.80	0.81	0.80
	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
R^2	0.89	0.89	0.89	0.90	0.90	0.90	0.90

Notes: NLLS estimates of $i_t = \rho i_{t-1} + (1-\rho)\{c + \beta E\pi_{t-1+h} + \gamma\widehat{y}_{t-1} + \xi E_t\} + \varepsilon_t$. Newey-West HAC standard errors are in parentheses. Inflation forecasts are obtained using BMA Phillips curve applied to "current vintage" data. See Section 5.2 for details. The interest rate i_t is the Federal Funds Rate for the US, overnight interest rate for Canada, 3 month TB rate for the UK, and Money Market rate for Germany. The output gap is defined as deviations from a quadratic trend over the last 20 years. The output gap for Germany is the official Bundesbank series. Inflation is the GDP deflator inflation for the US, UK, and Germany, and the Core CPI inflation for Canada. Square brackets mark "nowcast" of inflation (quarter t forecast as available at quarter t).

Table 4: US and UK real-time forward-looking Taylor rule estimates over different subsamples of data with inclusion of additional variables

Variable	Specification					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. U.S. subsamples	1982:1–1987:1			1987:1–2007:1		
Inflation forecast β	2.28	2.43	2.48	1.87	2.08	2.43
	(0.31)	(0.44)	(0.48)	(0.16)	(0.45)	(0.48)
Output gap γ	-0.06	-0.03	-0.03	0.59	0.80	1.39
	(0.05)	(0.09)	(0.09)	(0.10)	(0.14)	(0.28)
Output gap growth λ			0.07			2.81
			(0.26)			(0.76)
Smoothing ρ		0.25	0.27		0.79	0.86
		(0.13)	(0.13)		(0.04)	(0.04)
Const c	-0.26	-0.79	-0.96	0.17	-0.40	-0.91
	(0.96)	(1.27)	(1.38)	(0.53)	(1.17)	(1.31)
R^2	0.85	0.88	0.88	0.76	0.96	0.97
Panel B. U.K. full sample	Including 1987:2–1990:3			Excluding 1987:2–1990:3		
Inflation forecast β	1.36	1.77	1.39	1.47	1.37	1.45
	(0.22)	(0.35)	(0.24)	(0.36)	(0.28)	(0.31)
Output gap γ	0.44	0.38	0.43	0.12	0.11	0.21
	(0.22)	(0.34)	(0.23)	(0.26)	(0.34)	(0.35)
German interest rate ϕ	0.50		0.52		0.00	0.11
	(0.21)		(0.21)		(0.44)	(0.46)
DM/GBP change ξ		0.14	0.10	0.17		0.17
		(0.17)	(0.12)	(0.18)		(0.16)
Smoothing ρ	0.78	0.85	0.78	0.82	0.81	0.81
	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)
Const c	-0.53	-0.01	-0.70	0.85	1.17	0.53
	(0.95)	(1.19)	(0.99)	(1.11)	(1.86)	(2.03)
R^2	0.94	0.94	0.94	0.91	0.91	0.91

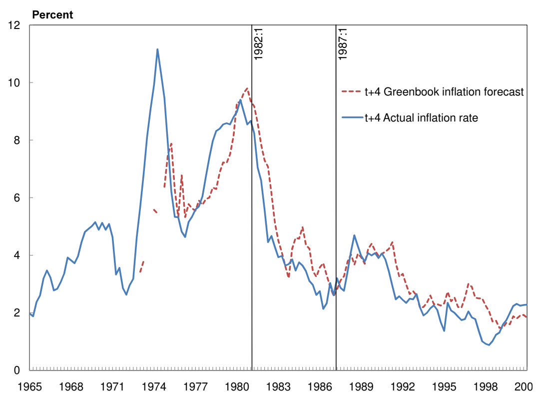
Notes: NLLS estimates of $i_t = \rho i_{t-1} + (1-\rho)\{c + \beta E\pi_{t-1+4} + \gamma\widehat{y}_{t-1} + \lambda\triangle\widehat{y}_{t-1+4} + \phi r^{GR} + \xi de_t\} + \varepsilon_t$. Newey-West HAC standard errors are in parentheses. Inflation forecasts are obtained using the BMA Phillips curve model applied to "current vintage" data. See Section 5.2 for details. the interest rate i_t is the Federal Funds Rate for the US, and 3 month TB rate for the UK. $de_t = 100\ln(e_t/e_{t-1})$ and e_t is the DM/GBP nominal exchange rate. The output gap is defined as deviations from a quadratic trend over the last 20 years. The UK full sample is 1983:3–1990:3 and 1992:4–2007:1, which excludes the period when the UK was a part of the EMS.

Table 5: Canadian and German forward-looking real-time Taylor rule estimates with inclusion of additional variables

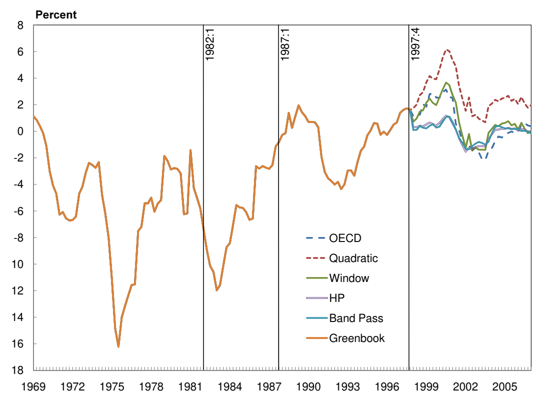
Variable	Specification				
	(1)	(2)	(3)	(4)	(5)
Panel A. Canada					
Inflation forecast β	1.35	1.37	0.72	1.60	1.74
	(0.31)	(0.32)	(0.22)	(0.92)	(0.94)
Output gap γ	-0.22	-0.20	-0.17	0.24	0.42
	(0.10)	(0.10)	(0.07)	(0.55)	(0.64)
CAD/USD change ξ		0.08			0.75
		(0.09)			(0.74)
Federal Funds Rate ϕ			0.82		
			(0.13)		
Smoothing ρ				0.91	0.91
				(0.06)	(0.06)
Const c	1.67	1.66	-0.45	0.88	0.81
	(0.72)	(0.73)	(0.62)	(2.47)	(2.47)
R^2	0.58	0.58	0.80	0.93	0.93
Panel B. Germany					
Inflation forecast β	1.16	0.70	2.74	2.25	2.17
	(0.35)	(0.48)	(1.01)	(0.85)	(0.79)
Output gap γ	0.18	0.30	0.78	1.20	1.17
	(0.08)	(0.08)	(0.44)	(0.63)	(0.60)
Money growth rate		-0.08		0.16	
		(0.16)		(0.29)	
Real DM/USD rate ζ				0.08	0.08
				(0.06)	(0.06)
Federal Funds Rate ϕ		0.25			
		(0.15)			
Smoothing ρ			0.90	0.89	0.88
			(0.04)	(0.04)	(0.04)
Const c	3.27	3.00	0.40	-4.74	-4.02
	(1.30)	(1.52)	(2.78)	(3.99)	(3.97)
R^2	0.28	0.41	0.95	0.95	0.95

Notes: NLLS estimates of $i_t = \rho i_{t-1} + (1-\rho)\{c + \beta E\pi_{t-1+h} + \gamma \widehat{y}_{t-1} + \phi r_t^{US} + \xi de_t + \zeta E_t\} + \varepsilon_t$, where $de_t = 100\ln(e_t/e_{t-1})$ and e_t is the CAD/USD nominal exchange rate. E_t is the DM/USD real exchange rate, defined as $E_t = e_t p_{t-1}^{GR}/p_{t-1}^{US}$, where e_t is the DM/USD nominal exchange rate and p is the GDP deflator price level. Newey-West HAC standard errors are in parentheses. Inflation forecasts are obtained using the BMA Phillips curve model applied to "current vintage" data. See Section 5.2 for details. The forecast horizon h is equal to $\{4\}$ for Canada and $\{5\}$ for Germany. For Canada, the interest rate i_t is the overnight rate, inflation is the core CPI year-over-year inflation rate, and the output gap is defined as deviations from a quadratic trend over the last 20 years. For Germany, the interest rate i_t is the Money Market rate, inflation is the year-over-year GDP deflator inflation rate, and the output gap is the official Bundesbank series.

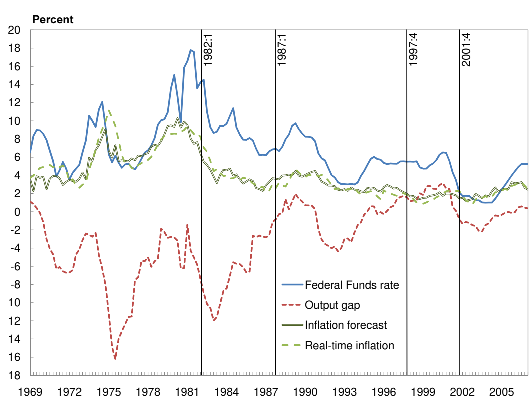
Figure 1: U.S.



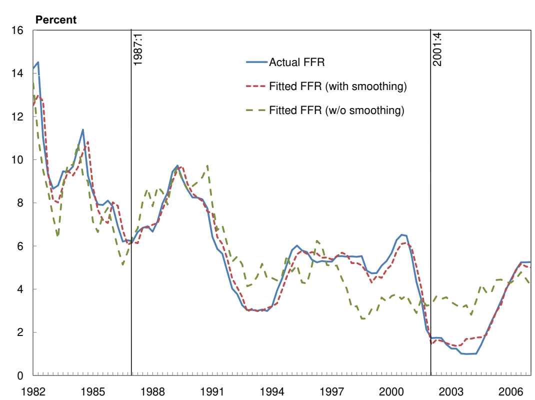
a. Greenbook forecast and actual inflation t+4 periods ahead



b. Different measures of output gap



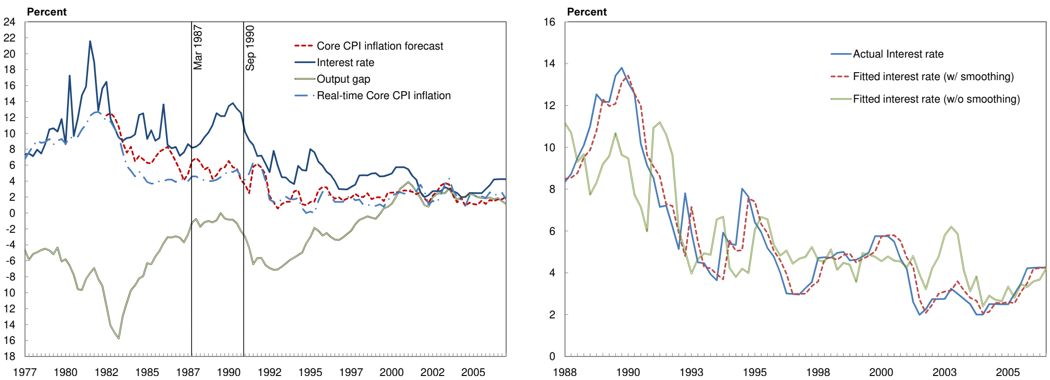
c. Monetary policy determinants



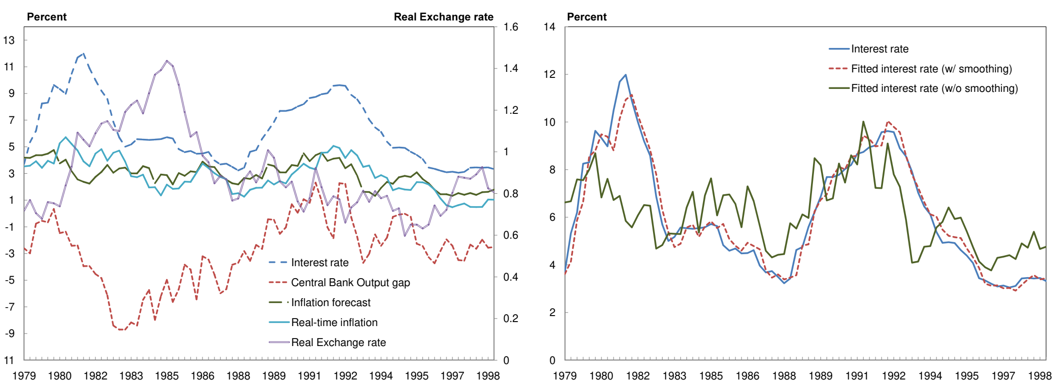
d. Actual and fitted Federal Funds rate

Notes: The interest rate is the Federal Funds rate in the 3rd month of the quarter. Inflation is defined as $h = 4$ quarters ahead year-over-year GDP deflator growth rate forecast. The output gap is defined as deviations from a quadratic trend over the last 20 years. Whenever available, Greenbook data is used.

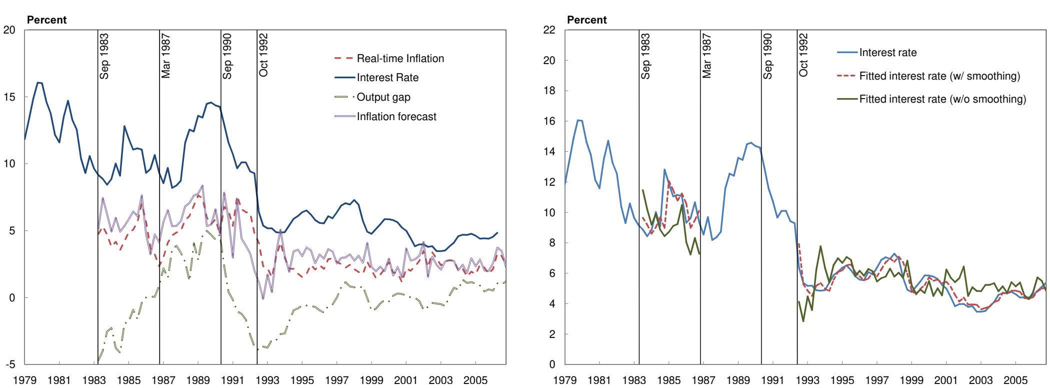
Figure 2: Monetary policy determinants and Taylor rules fit



a. Canada



b. Germany



c. U.K.

Notes: The inflation forecast horizon is one year for the US and Germany, and six months for Canada and the UK. Inflation is the GDP deflator inflation for the U.K., and Germany, and the Core CPI inflation for Canada. For Canada and the U.K., the output gap is defined as deviations from a quadratic trend over the last 20 years; for Germany, the output gap is the official Bundesbank series.

Appendices

Efficiency tests.

$$
\begin{aligned}
\text{Test 1: } z &= \frac{\sum_{i=1}^{N} R_i - \frac{1}{2}}{\sqrt{\frac{N(N+1)(2N+1)}{6}}} \sim N(0,1) \\
\text{Test 2: } r_t^f &= \alpha + \varepsilon_t \\
\text{Test 3: } r_t^f &= \alpha + \beta x_t^{t+1} + \varepsilon_t \\
\text{Test 4: } r_t^f &= \alpha + \beta x_t^{t+1} + \sum_{i=1}^{4} \lambda Q_t^i + \delta t + \varepsilon_t \\
\text{Test 5: } r_t^f &= \alpha + \beta x_t^{t+1} + \sum_{i=1}^{4} \gamma_i r_{t-i}^i + \sum_{i=1}^{4} \lambda Q_t^i + \delta t + \varepsilon_t
\end{aligned}
$$

Table A-1: "Current vintage," "Diagonals," and "First release" specifications of real-time data by the example of the U.S. annualized quarterly GDP deflator inflation rate as of the fourth quarter of 1999 (1999:Q4).

Calendar Date	*Vintage (release) dates*							
...	...	1998:Q3	1998:Q4	1999:Q1	1999:Q2	1999:Q3	1999:Q4	2000:Q1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	–
1994:03	...	2.56	2.56	2.56	2.56	2.56	$2.33^{\triangle}$	–
1994:04	...	2.65	2.65	2.65	2.65	2.65	$1.84^{\triangle}$	–
1995:01	...	2.49	2.49	2.49	2.49	2.49	$2.89^{\triangle}$	–
1995:02	...	1.83	1.83	1.83	1.83	1.83	$1.63^{\triangle}$	–
1995:03	...	1.90	1.90	1.90	1.90	1.90	$1.75^{\triangle}$	–
1995:04	...	2.02	2.02	2.02	2.02	2.02	$1.90^{\triangle}$	–
1996:01	...	2.28	2.28	2.28	2.28	2.28	$2.44^{\triangle}$	–
1996:02	...	1.20	1.20	1.20	1.20	1.20	$1.27^{\triangle}$	–
1996:03	...	1.81	1.81	1.81	1.81	1.81	$1.71^{\triangle}$	–
1996:04	...	1.78	1.78	1.78	1.78	1.78	$1.41^{\triangle}$	–
1997:01	...	2.80	2.80	2.80	2.80	2.80	$2.37^{\triangle}$	–
1997:02	...	1.54	1.54	1.54	1.54	1.54	$1.51^{\triangle}$	–
1997:03	...	$1.18^{\diamond}$	1.18	1.18	1.18	1.18	$1.14^{\triangle}$	–
1997:04	...	$1.17^{\diamond}$	$1.17^{\diamond}$	1.17	1.17	1.17	$1.18^{\triangle}$	–
1998:01	...	$0.84^{\diamond}$	$0.84^{\diamond}$	$0.84^{\diamond}$	0.84	0.84	$0.90^{\triangle}$	–
1998:02	–	$0.85^{\diamond\star}$	$0.87^{\diamond}$	$0.87^{\diamond}$	$0.87^{\diamond}$	0.87	$1.27^{\triangle}$	–
1998:03	–	–	$0.82^{\diamond\star}$	$0.98^{\diamond}$	$0.98^{\diamond}$	$0.98^{\diamond}$	$1.52^{\triangle}$	–
1998:04	–	–	–	$0.83^{\diamond\star}$	$0.82^{\diamond}$	$0.82^{\diamond}$	$1.02^{\triangle\diamond}$	–
1999:01	–	–	–	–	$1.40^{\diamond\star}$	$1.59^{\diamond}$	$1.93^{\triangle\diamond}$	–
1999:02	–	–	–	–	–	$1.56^{\diamond\star}$	$1.37^{\triangle\diamond}$	–
1999:03	–	–	–	–	–	–	$0.94^{\triangle\diamond\star}$	–
1999:04	–	–	–	–	–	–	–	–

Notes: $^{\triangle}$s mark "current vintage" data, $^{\diamond}$s mark "diagonals" data, and *s mark "first releases" data. "Diagonals" data is shown for the case when 4 lags of unemployment rate are used. Three dots represent data which is (generally) available in 1999:Q4, but is not displayed in this table. "–" means that the data is not available in 1999:Q4.

Table A-2: Efficiency test results with actuals defined as 2007:Q2 vintage

	Wilcoxon Ranking Test	Zero mean t-test	Mincer–Zarnowitz	Quarterly dummies and Time trend	Past revisions
	(1)	(2)	(3)	(4)	(5)
		Panel A. Country: US			
GDP Growth	4.55	2.93	51.07	62.78	64.92
GDP Inflation	1.56	1.11	13.25	24.95	30.62
CPI Inflation	0.63	0.24	0.07	7.44	9.24
Unemployment	2.53	1.63	4.00	7.58	17.01
		Panel D. Country: Canada			
GDP Growth	4.35	2.88	29.66	28.64	31.47
GDP Inflation	2.22	0.7	14.02	23.17	23.88
CPI Inflation	-0.15	-0.27	0.13	0.31	1.82
Unemployment	0.55	-1.21	3.32	8.86	12.72
Core CPI Inflation	6.28	1.14	2.22	7.43	7.68
		Panel B. Country: Germany			
GDP Growth	2.57	1.88	21.85	19.48	24.05
GDP Inflation	0.42	-0.15	17.92	17.81	19.62
CPI Inflation	-0.84	-2.08	4.87	9.64	20.86
Money Growth	-1.62	-2.76	13.88	34.51	45.09
		Panel C. Country: UK			
GDP Growth	4.69	4.96	53.52	53.86	59.63
GDP Inflation	2.69	1.74	69.01	92.84	93.36

Notes: The series being tested is "Revisions" defined as "Actuals–Real-time." Regression-based tests (2)–(5) employ robust Newey-West standard errors. Test statistics for (3)–(5) come from LR-tests for joint insignificance of coefficients (including the constant term). (3) assumes the base specification (2) and adds the series of first-releases. (4) assumes (3) plus quarterly dummies and a linear time trend. (5) assumes (4) and adds 4 lags of past revisions (Eq. **??**). 5% critical values for (1)-(5) are 1.96, 1.96, 5.99, 12.6 and 18.3, respectively.

Table A-3: The relative performance of different types of models and real-time data in reproducing Greenbook h-quarter-ahead inflation forecasts during 1987:2–2001:4 (second half of the 1974:1–2001:4 sample). Performance is evaluated based on RMSPE

	Univariate				Bivariate		Multivariate	
h-steps	RW	DAR(p)	IAR(p)	ARMA (1,1)	CG-VAR	Phillips Curve	Clustering	Data-rich BMA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Current-vintage								
1	0.395=1.00	0.77	0.77	0.97	0.86	0.76	0.77	0.76
2	0.618=1.00	0.81	0.80	0.91	1.00	0.77	0.81	0.82
3	0.814=1.00	0.86	0.87	0.84	1.10	0.78	0.83	0.84
4	0.971=1.00	0.84	0.86	0.78	1.16	0.74	0.76	0.82
5	1.099=1.00	0.84	0.93	0.85	1.16	0.73	0.77	0.80
Panel B. Diagonals								
1	0.395=1.00	1.02	0.95	1.14	1.15	0.97	1.51	0.93
2	0.618=1.00	1.07	1.02	0.97	1.18	1.12	1.03	1.05
3	0.814=1.00	1.22	1.11	0.90	1.26	1.22	1.05	1.12
4	0.971=1.00	1.25	1.07	0.83	1.23	1.20	1.05	1.07
5	1.099=1.00	1.52	1.26	0.83	1.24	1.22	1.11	1.12
Panel C. Diagonals								
1	0.395=1.00	1.09	1.10	1.14	1.15	1.00	0.95	1.13
2	0.618=1.00	1.20	1.24	0.97	1.18	1.10	1.06	1.15
3	0.814=1.00	1.39	1.43	0.90	1.26	1.17	1.06	1.21
4	0.971=1.00	1.36	1.42	0.83	1.23	1.11	1.03	1.09
5	1.099=1.00	1.68	1.71	0.84	1.24	1.14	1.10	1.17

Notes: RMSPE stands for "Root Mean Square Prediction Error." Column (1) RW reports the absolute RMSPE; models (2)-(8) report ratio of their RMSPE to that of a RW, with values lower than 1 meaning that a model outperforms the RW. RW stays for random walk no-change forecast. The lag length p is fixed at $p = 8$ for Panel A, and at $p = 4$ for Panels B and C. IAR stays for iterative autoregression. CG-VAR is a constant gain VAR considered in Branch and Evans (2006). Phillips Curve is a variable lag length ADL model in output growth and inflation with the forecast produced using Bayesian model averaging (BMA). Clustering is a Aiolfi and Timmermann (2006) technique with the cluster size K=5. Data-rich BMA comes from Faust and Wright (2007). Refer to Section 3 for further details. A star "*" denotes best performing models at a given forecasting horizon. "Current-vintage," "Diagonals," and "First release" are all types of real-time data, which uses only information available to forecasters at the time they were making forecasts. For explanation of the difference between there three types of data, refer to Table A-1.

Table A-4: The relative performance of different types of models and real-time data in reproducing Greenbook h-quarter-ahead inflation forecasts during 1974:1–2001:4. Performance is evaluated based on RMSPE. Laglength $p = 4$.

	Univariate				Bivariate		Multivariate	
h-steps	RW	DAR(4)	IAR(4)	ARMA (1,1)	CG-VAR	Phillips Curve	Clustering	Data-rich BMA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Current-vintage								
1	0.395=1.00	1.08	1.11	1.02	0.90	0.90	0.76	0.76
2	0.618=1.00	1.02	1.25	1.08	1.05	0.96	0.85	0.84
3	0.814=1.00	1.02	1.37	0.98	1.17	1.00	0.91	0.91
4	0.971=1.00	1.10	1.53	0.97	1.28	1.10	1.00	1.02
5	1.099=1.00	1.00	1.54	0.89	1.59	1.00	0.95	1.01
Panel B. Diagonals								
1	0.395=1.00	1.03	1.02	0.97	1.07	0.89	0.84	0.84
2	0.618=1.00	1.18	1.16	0.95	1.23	1.02	1.03	1.04
3	0.814=1.00	1.32	1.30	0.92	1.35	1.09	1.06	1.12
4	0.971=1.00	1.53	1.46	0.93	1.44	1.12	1.05	1.15
5	1.099=1.00	1.61	1.48	0.89	1.45	1.12	1.05	1.25
Panel C. First-release								
1	0.395=1.00	1.06	1.06	0.97	1.07	0.95	0.97	0.98
2	0.618=1.00	1.20	1.24	0.95	1.23	1.05	1.07	1.10
3	0.814=1.00	1.36	1.43	0.92	1.35	1.11	1.09	1.16
4	0.971=1.00	1.58	1.64	0.93	1.44	1.12	1.06	1.21
5	1.099=1.00	1.70	1.70	0.89	1.45	1.10	1.04	1.26

Notes: RMSPE stands for "Root Mean Square Prediction Error." Column (1) RW reports the absolute RMSPE; models (2)-(8) report ratio of their RMSPE to that of a RW, with values lower than 1 meaning that a model outperforms the RW. RW stays for random walk no-change forecast. The lag length p is fixed at $p = 8$ for Panel A, and at $p = 4$ for Panels B and C. IAR stays for iterative autoregression. CG-VAR is a constant gain VAR considered in Branch and Evans (2006). Phillips Curve is a variable lag length ADL model in output growth and inflation with the forecast produced using Bayesian model averaging (BMA). Clustering is a Aiolfi and Timmermann (2006) technique with the cluster size K=5. Data-rich BMA comes from Faust and Wright (2007). Refer to Section 3 for further details. A star "*" denotes best performing models at a given forecasting horizon. "Current-vintage," "Diagonals," and "First release" are all types of real-time data, which uses only information available to forecasters at the time they were making forecasts. For explanation of the difference between there three types of data, refer to Table A-1.

Table A-5: Relative performance of different types of models and real-time data in reproducing Greenbook h-quarter-ahead inflation forecast during 1974:1-2001:4. Performance is evaluated based on RMSPE. Laglength $p = 8$.

	Univariate				Bivariate		Multivariate	
h-steps	RW	DAR(8)	IAR(8)	ARMA (1,1)	CG-VAR	Phillips Curve	Cluste-ring	Data-rich BMA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Current-vintage								
1	0.395=1.00	0.76	0.75	1.02	0.86	0.79	0.76	0.80
2	0.618=1.00	0.85	0.85	1.08	1.12	0.84	0.87	0.92
3	0.814=1.00	0.91	0.91	0.98	1.28	0.87	0.91	0.98
4	0.971=1.00	1.05	1.00	0.97	1.50	0.95	1.00	1.14
5	1.099=1.00	1.03	0.95	0.89	1.56	0.84	0.95	1.10
Panel B. Diagonals								
1	0.395=1.00	1.01	1.00	0.97	1.35	0.93	0.84	0.98
2	0.618=1.00	1.39	1.25	0.95	1.49	1.20	1.03	1.39
3	0.814=1.00	1.74	1.45	0.92	1.65	1.40	1.06	1.77
4	0.971=1.00	2.23	1.72	0.93	1.76	1.51	1.05	2.19
5	1.099=1.00	2.57	1.78	0.89	1.88	1.57	1.05	2.43
Panel C. First-release								
1	0.395=1.00	1.13	1.13	0.97	1.35	1.04	0.97	1.12
2	0.618=1.00	1.33	1.31	0.95	1.49	1.23	1.07	1.37
3	0.814=1.00	1.70	1.56	0.92	1.65	1.40	1.09	1.84
4	0.971=1.00	2.17	1.86	0.93	1.76	1.47	1.06	2.22
5	1.099=1.00	2.51	2.01	0.89	1.88	1.53	1.04	2.47

Notes: RMSPE stays for "Root Mean Square Prediction Error." First column (1) RW reports absolute RMSPE; models (2)-(8) report ratio of their RMSPE to that of a RW, with values lower than 1 meaning that a model outperforms the RW RW stays for random walk no-change forecast. IAR stays for iterative autoregression. CG-VAR is a constant gain VAR considered in Branch and Evans (2006). Phillips Curve is a variable lag length Phillips curve model in output growth and inflation with a forecast produced using Bayesian model averaging (BMA). Clustering is a Aiolfi and Timmermann (2006) technique with cluster size K=5. Data-rich BMA comes from Faust and Wright (2007). Refer to Section 3 for further details. Star "*" denotes the best performing model at a given forecasting horizon. "Current-vintage," "Diagonals," and "First release" are all types of real-time data, which uses only information available to forecasters at the time they were making forecasts. For explanation of differences between there three types of data, refer to Table A-1.

Table A-6: Comparison of forward-looking U.S. Taylor rule estimates of inflation coefficient β over 1979:3–1997:4 sample for different expected inflation series and forecast horizons

Horizon h	1. Greenbook forecast	2. This study forecast	3. Actuals at time $t+h$	
			GMM	2SLS
-1	2.32	2.32	1.69	2.19
	0.35	0.35	0.70	0.41
[0]	2.25	2.32	-0.50	2.43
	0.35	0.36	1.35	0.40
1	2.39	2.39	2.61	2.89
	0.40	0.39	0.34	0.46
2	2.51	2.50	0.08	2.93
	0.44	0.43	0.96	0.58
3	2.65	2.72	-0.13	2.93
	0.41	0.41	0.95	0.64
4	2.82	2.82	1.18	3.60
	0.38	0.36	1.06	0.91

Notes: GMM and IV estimates of $i_t = \rho i_{t-1} + (1-\rho)\{c + \beta E\pi_{t-1+4} + \gamma \widehat{y}_{t-1} + \lambda \triangle \widehat{y}_{t-1+4}\} + \varepsilon_t$. Newey-West HAC standard errors are in parentheses. Interest rate i_t is the Federal Funds rate. Output gap is defined as deviations from quadratic trend over last 20 years. Square brackets mark "nowcast" of inflation (quarter t forecast as available at quarter t). List of instruments includes 4 lags of interest rate i_t, 4 lags of inflation rate π_t, 4 lags of output gap $\widehat{y}$, and 4 lags of the output gap growth $\triangle \widehat{y}$. (2) uses conditional forecasts of inflation constructed in the way described in Section 3. (3) replaces them with actual, ex-post realized values of inflation, with estimation performed by either GMM or 2SLS. To eliminate discrepancies due to statistical revisions, instead of the today's vintage of data, I use the leads of the "first release" inflation series as actuals. Finally, (1) uses original Greenbook forecasts to obtain "true" benchmark parameters. I have to end the sample in 1997:4 as this is the last point where the Greenbook output gap data is publicly available so far.

Table A-7: Canadian real-time Taylor rule estimates over 1991:1–2007:1

Gap:	Window	Quadratic	HP	Band-pass
	(1)	(2)	(3)	(4)
Panel A. Backward-looking Taylor rule ($h = 0$)				
Inflation β	0.28	0.27	0.36	0.36
	0.29	0.28	0.38	0.39
Output gap γ	-0.26	-0.24	-0.29	-0.37
	0.10	0.09	0.41	0.44
Const c	3.75	4.83	3.67	3.62
	0.65	0.82	0.80	0.79
R^2	0.31	0.32	0.12	0.13
Panel B. Forward-looking Taylor rule ($h = 10$)				
Inflation forecast β	1.14	1.13	1.27	1.26
	0.20	0.20	0.21	0.23
Output gap γ	-0.26	-0.24	-0.75	-0.87
	0.06	0.06	0.25	0.29
Const c	1.34	2.44	0.82	0.77
	0.57	0.69	0.65	0.68
R^2	0.63	0.64	0.52	0.52

Notes: Least squares estimates of $i_t = c + \beta E\pi_{t-2+h} + \gamma\widehat{y}_{t-2} + \varepsilon_t$. Newey-West HAC standard errors are in parentheses. Expectations are formed using "current vintage" data. See Table A-1 for details. Interest rate i_t is the middle month overnight rate. Inflation is the core CPI year-over-year inflation rate. "Window" assumes quadratic detrending over last 20 years.

Table A-8: German real-time backward-looking Taylor rule estimates over 1979:1–1998:4

Variable	Specification					
	(1)	(2)	(3)	(4)	(5)	(6)
Inflation β	0.78	1.19	1.17	1.23	1.34	1.38
	0.23	0.27	0.49	0.10	0.10	0.14
Output gap γ	0.95	0.99	0.79	0.51	0.51	0.22
	0.16	0.29	0.37	0.05	0.06	0.07
Real exchange rate ξ	0.05	0.08		0.05	0.05	
	0.02	0.03		0.01	0.01	
Federal Funds Rate λ	0.41			0.10		
	0.12			0.07		
Smoothing ρ	0.79	0.80	0.87			
	0.04	0.06	0.06			
Const c	-0.98	-1.50	5.14	-0.73	-0.84	2.89
	1.34	2.12	1.86	0.72	0.84	0.42
R^2	0.96	0.95	0.94	0.79	0.78	0.68

Notes: NLLS estimates of $i_t = \rho i_{t-1} + (1-\rho)\{c + \beta E\pi_{t-1} + \gamma\widehat{y}_{t-1} + \xi\triangle E_t + \lambda r_t^{US}\} + \varepsilon_t$. Newey-West HAC standard errors are in parentheses. Interest rate i_t is the Money Market Rate. Output gap is real-time Bundesbank's estimates of the output gap.

Table A-9: UK real-time backward-looking Taylor rule estimates with and without interest rate smoothing and various output gaps

	Quadratic		Band-pass		HP	
	(1)	(2)	(3)	(4)	(5)	(6)
Inflation β	1.29	0.95	1.30	0.90	1.26	0.85
	0.20	0.86	0.20	0.68	0.18	0.56
Output gap γ	-0.04	0.46	1.10	3.35	1.14	2.86
	0.17	0.91	0.50	1.23	0.48	0.80
Smoothing ρ	–	0.91	–	0.88	–	0.84
		0.04		0.04		0.04
Const c	2.57	3.25	2.64	3.51	2.73	3.66
	0.52	2.22	0.53	1.73	0.47	1.41
R^2	0.46	0.89	0.53	0.90	0.58	0.91

Notes: NLLS estimates of $i_t = \rho i_{t-1} + (1-\rho)\{c + \beta\pi_{t-1} + \gamma\widehat{y}_{t-1}\} + \varepsilon_t$. Newey-West HAC standard errors are in parentheses. Interest rate i_t is 3-month Treasury Bill rate. Inflation is defined as year-over-year GDP deflator growth rate. Sample period is 1983:3–1987:1 and 1992:4–2007:1.

Table A-10: UK real-time forward-looking Taylor rule estimates over various subsamples and definitions of the output gap

	Full sample 1983:3–2007:1			Except 1990:4–1992:3			Except 1987:2–1992:3		
Variable	Quad-ratic	Band-pass	HP	Quad-ratic	Band-pass	HP	Quad-ratic	Band-pass	HP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inflation β	1.54	1.69	1.66	1.70	1.90	1.89	1.37	1.24	1.01
	0.36	0.41	0.42	0.31	0.44	0.44	0.30	0.47	0.33
Output gap γ	0.34	0.07	0.31	0.41	0.11	0.14	0.13	0.60	1.45
	0.35	1.43	1.21	0.32	1.81	1.34	0.26	1.21	0.67
Smoothing ρ	0.87	0.87	0.88	0.85	0.86	0.86	0.81	0.81	0.81
	0.04	0.05	0.05	0.05	0.06	0.06	0.06	0.05	0.04
Const c	0.92	0.31	0.44	0.27	-0.49	-0.46	1.21	1.61	2.47
	1.24	1.47	1.53	1.09	1.53	1.57	0.96	1.52	1.06
R^2	0.94	0.94	0.94	0.94	0.94	0.94	0.91	0.91	0.91

Notes: NLLS estimates of $i_t = \rho i_{t-1} + (1-\rho)\{c + \beta E\pi_{t-1+4} + \gamma\widehat{y}_{t-1}\} + \varepsilon_t$. Newey-West HAC standard errors are in parentheses. Expectations are formed using "current vintage" data. See Table A-1 for details. 4-quarter-ahead corresponds to $t+3$ calendar date to account for 1-quarter lag in reporting real-time data. Interest rate i_t is 3-month Treasury Bill rate. Inflation is defined as year-over-year GDP deflator growth rate.
NLLS estimates of $i_t = \rho i_{t-1} + (1-\rho)\{c + \beta E\pi_{t+h} + \gamma\widehat{y}_t\} + \varepsilon_t$. Newey-West HAC standard errors are in parentheses. Expectations are formed using "current vintage" data. See Table A-1 for details. 4-quarter-ahead corresponds to $t+3$ calendar date to account for 1-quarter lag in reporting real-time data. Interest rate i_t is 3-month Treasury Bill rate. Inflation is defined as year-over-year GDP deflator growth rate.

Table A-11: Efficiency test results with actuals defined as the second revision

	Wilcoxon Ranking Test	Zero mean t-test	Mincer–Zarnowitz	Quarterly dummies and Time trend	Past revisions
	(1)	(2)	(3)	(4)	(5)
			Panel A. Country: US		
GDP Growth	1.40	1.14	2.10	2.18	4.97
GDP Inflation	2.22	2.26	7.68	10.43	11.98
CPI Inflation	1.40	0.73	4.97	8.85	16.20
Unemployment	4.96	-0.44	0.15	2.60	2.71
			Panel D. Country: Canada		
GDP Growth	0.13	0.48	3.49	4.94	6.84
GDP Inflation	0.28	-0.26	0.11	10.90	13.05
CPI Inflation	6.65	-1.21	1.73	5.78	8.85
Unemployment	5.32	-1.07	3.76	5.01	9.08
Core CPI Inflation	7.56	-1.12	2.00	9.49	10.23
			Panel B. Country: Germany		
GDP Growth	3.17	2.81	11.43	11.06	13.25
GDP Inflation	-0.86	-1.04	1.09	6.03	8.21
CPI Inflation	-0.24	-2.05	4.43	9.51	21.04
Money Growth	2.20	-1.15	7.02	6.03	10.68
			Panel C. Country: UK		
GDP Growth	2.72	2.78	11.55	14.36	16.92
GDP Inflation	3.13	1.80	83.43	110.00	110.80

Notes: The series being tested is "Revisions" defined as "Actuals–Real-time." Regression-based tests (2)–(5) employ robust Newey-West standard errors. Test statistics for (3)–(5) come from LR-tests for joint insignificance of coefficients (including the constant term). (3) assumes the base specification (2) and adds the series of first-releases. (4) assumes (3) plus quarterly dummies and a linear time trend. (5) assumes (4) and adds 4 lags of past revisions (Eq. **??**). 5% critical values for (1)-(5) are 1.96, 1.96, 5.99, 12.6 and 18.3, respectively.

Table A-12: The relative performance of different types of models and real-time data in forecasting actual inflation h quarters ahead during 1974:1–2001:4. Performance is evaluated based on RMSPE

	Univariate				Bivariate		Multivariate	
h-steps	RW	DAR(p)	IAR(p)	ARMA (1,1)	CG-VAR	Phillips Curve	Clustering	Data-rich BMA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Current-vintage								
1	0.516=1.00	0.85	0.85	0.96	0.93	0.85	0.85	0.91
2	0.830=1.00	0.92	0.89	0.99	0.99	0.87	0.87	0.98
3	1.096=1.00	0.96	0.91	0.93	1.03	0.87*	0.88*	0.99
4	1.384=1.00	1.02	0.95	0.90	1.06	0.88	0.90	1.06
5	1.567=1.00	1.01	0.95	0.88	1.07	0.83*	0.88	1.02
Panel B. Diagonals								
1	0.516=1.00	0.92	0.91	0.93	0.93	0.84*	0.82*	0.84*
2	0.830=1.00	0.98	0.96	0.93	0.91	0.85*	0.86*	0.88
3	1.096=1.00	1.06	1.03	0.93	0.98	0.88*	0.87*	0.89
4	1.384=1.00	1.14	1.10	0.94	1.01	0.86*	0.86*	0.86*
5	1.567=1.00	1.18	1.15	0.94	1.04	0.86	0.85*	0.91
Panel C. First-release								
1	0.516=1.00	0.93	0.93	0.93	0.93	0.86	0.85	0.88
2	0.830=1.00	0.99	0.99	0.92	0.91	0.85*	0.86*	0.91
3	1.096=1.00	1.09	1.11	0.93	0.98	0.88*	0.88*	0.92
4	1.384=1.00	1.19	1.21	0.94	1.01	0.87*	0.87*	0.90
5	1.567=1.00	1.25	1.29	0.94	1.04	0.85*	0.84*	0.93

Notes: RMSPE stands for "Root Mean Square Prediction Error." Column (1) RW reports the absolute RMSPE; models (2)-(8) report ratio of their RMSPE to that of a RW, with values lower than 1 meaning that a model outperforms the RW. RW stays for random walk no-change forecast. The lag length p is fixed at $p = 8$ for Panel A, and at $p = 4$ for Panels B and C. IAR stays for iterative autoregression. CG-VAR is a constant gain VAR considered in Branch and Evans (2006). Phillips Curve is a variable lag length ADL model in output growth and inflation with the forecast produced using Bayesian model averaging (BMA). Clustering is a Aiolfi and Timmermann (2006) technique with the cluster size K=5. Data-rich BMA comes from Faust and Wright (2007). Refer to Section 3 for further details. A star "*" denotes best performing models at a given forecasting horizon. Actual data is the second revision in the dataset. "Current-vintage," "Diagonals," and "First release" are all types of real-time data, which uses only information available to forecasters at the time they were making forecasts. For explanation of the difference between there three types of data, refer to Table A-1.