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

Alex Nikolsko–Rzhevskyy†

October 25, 2010

Abstract

I propose a methodology for estimating forward-looking Taylor rules in real time when forward-looking real-time central bank data is unavailable. The methodology consists of choosing appropriate models to closely replicate U.S. Greenbook forecasts, and then applying these models to Canada, Germany, and the U.K. The results show that the Greenbook output gap series is well described by rolling window linear 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 years and the output gap coefficient is insignificant.

JEL Classification: E58, E52, C53
Keywords: real-time data, Taylor rule, monetary rules, inflation forecasts, output gap.

* I thank Olivier Coibion, Dean Croushore, Adriana Fernandez, Andrew Hussey, David Kemme, Chris Murray, Tanya Molodtsova, Simon van Norden, Masao Ogaki, David Papell, Elena Pesavento, Jeremy Piger, Ruxandra Prodan, Tara Sinclair, William Smith, two anonymous referees, and participants at presentations at the 17^{th} Midwest Econometrics Group Meeting, 79^{th} Annual Meetings of the Southern Economic Association, Fordham University, and Emory University for helpful comments and discussions. I am thankful to Athanasios Orphanides for sharing his data.

† Correspondence: Department of Economics, University of Memphis, Memphis, TN 38152. Tel.: (832) 858-2187. Email: alex.rzhevskyy@ gmail.com. Web: www.nikolsko-rzhevskyy.com

1 Introduction

During the last decade, simple policy rules have gained increasing popularity as a standard way to monitor and evaluate the behavior of central banks. This research originated with 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. Second, Orphanides (2001, 2003, 2004) 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 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 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 beyond the U.S.

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 real-time Taylor rules for the U.S. (including the 2002–2007 period) and three other countries: Canada, the U.K., and Germany, expanding the existing research. The methodology consists of four steps. First, I search for a model or a set of models that 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.[1] Finally, after constructing inflation forecasts and output gap estimates, I estimate forward-looking monetary policy reaction functions for all four central banks.

To replicate the Greenbook output gap, I apply six popular detrending techniques, including both methods with deterministic and stochastic trends. To match the Fed's internal inflation forecasts, I employ eight univariate, bivariate, and multivariate forecasting models. The data show that the U.S. output gap series is well-described by the 20-year rolling window linear 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.

Monetary policy estimation results show that the U.S. full sample monetary policy estimates closely resemble those of pre-2002, where actual Greenbook data is available. The Taylor rule estimated over the entire sample appears to be forward-looking, 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 decreases, indicating that the typical estimate from a "backward-looking" specification might be biased upwards.

German monetary policy exhibits 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

[1]The issue of transferability of the U.S. models to the rest of the countries is controversial. However, evidence shows that many Bundesbank, Bank of England, and Bank of Canada officials have prior experience working for the Fed and/or hold degrees from the leading U.S. universities. Thus, we expect them to be using output gap estimation and inflation forecasting techniques that are similar to those used by the Fed. In addition, to construct the out-of-sample forecasts, the models are first estimated separately for each of the countries in-sample using their real-time datasets. Therefore, the estimated coefficients would generally be different from country to country, meaning that the models could place different weights on different variables. This, at least partially, takes into account that different economies might face different economic conditions and have different variables in play.

at middle-term forecast horizons of about 1/2 years. Both monetary rules are characterized by small and insignificant output gap coefficients. Estimating Taylor rules for the U.K. and 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 of the four countries, showing that the Fed, the Bank of Canada, the Bundesbank, and the Bank of England obeyed the Taylor principle.

The remainder of the paper proceeds 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 to make predictions, and describe competing models of inflation and output gap. Section 4 contains a description of the data, 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 a 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 Taylor rule that encompasses either contemporaneous or forward-looking policy making can be written as:

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

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 gradually adjusts the actual interest rate, i, 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 $h = 0$, none of the right hand side variables of Eq. 1 are 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. After allowing for additional policy determinants x_t to affect monetary decisions, the policy rule takes the following form:

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

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, and finding good instruments is problematic. Finally, the realized values of inflation are the "effect" of the Fed's policy, not the "cause." Therefore, they might not be appropriate in the interest rate reaction function in the first place. To illustrate, 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 since the early 1980s, when price stability became one of the Fed's main concerns, 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 when 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, real-time forecasts must be considered.

3 Methods

3.1 Output gap estimation.

We start by defining an appropriate measure of the output gap and developing a way to estimate its value in each period $E(\hat{y}_t|\Omega_t)$ given the real-time data available to policymakers in various countries. One way to define the output gap is as 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.[2] Thus, following the discussion above, I apply six different detrending methods to each vintage v of the U.S. real-time real GDP data:[3]

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, $\widehat{y}_t$. To add additional flexibility to the trend and to improve its ability to capture possible structural breaks, I also use rolling window estimation, where only the last n values of GDP (instead of the entire vintage) are used for estimation.

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. In addition to OLS estimation, 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 for real-time datasets. To cope with this issue I follow Watson (2007) by using an

[2]Although it utilizes only limited amount of information, this approach is arguably the most common way of measuring potential output, employed by Taylor (1993), Clarida, Gali, and Gertler (1998), Taylor (1999), Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) and many others.

[3]For example, potential output for the U.S. in 1965:Q4 (the first available vintage) is calculated using only data available in 1965:Q4. For each subsequent quarter, an additional observation is added until the last vintage in 2007:Q1.

AR(8) growth rate model to extend the log of real GDP series by $K = 100$ datapoints in both directions before applying the filter.[4]

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 $\widehat{y}_t = y_t - \tau_t$ and $\lambda = 1600$. To account for end-of-sample distortions created by the filter, a backcast and forecast of 12 observations is made following Clausen and Meier (2005).

5. *Unobserved Component (UC) model.* This 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 AR(2) process. The UC model imposes a restriction of zero correlation between trend and cycle innovations.

6. *Beveridge-Nelson decomposition (BN).* Here, I assume y_t follows ARIMA(2,1,2) which is identical in the setup of the UC model, but relaxing the assumption of zero correlation between trend and cycle innovations. See Morley, Nelson, and Zivot (2003) for details.

The output gap series $(\widehat{y}_{t-1}|y_{t-1})$ from each model is evaluated based on its 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 several popular inflation-forecasting models, extending them to estimate over the traditional "vintages" data, and over "diagonals" and "first-release" data as well.[5,6]

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

[5] If the value of a variable X_t at time k as it is thought of in vintage v is defined as x_k^v, then the ith lag of the variable X_t is defined as this sequence of values: $\{x_{1-i}^t, \ldots, x_{t-1-i}^t, x_{t-i}^t\}$ for "vintages," $\{x_{1-i}^{1-i}, \ldots, x_{t-1-i}^{t-1-i}, x_{t-i}^{t-i}\}$ for "first releases," and $\{x_{1-i}^1, \ldots, x_{t-1-i}^{t-1}, x_{t-i}^t\}$ for "diagonals." See Koenig, Dolmas, and Piger (2003) for details. Corradi, Fernandez and Swanson (2007) argue that "vintages" is usually the data used by the Federal Reserve and other forecasters.

[6] Another possibility would be to use survey forecasts instead. Indeed, experimenting with the Survey of Professional Forecasters (SPF) forecasts suggests that they are not very different from the Greenbook forecasts. However, I was unable to find comparable survey data for the rest of the countries covering the time periods I am interested in.

The models can be divided into three groups: simple univariate models, bivariate models (usually in inflation and output growth), and atheoretical multivariate models. Whenever possible, the original estimation techniques are enhanced by allowing forecast aggregation as aggregating forecasts over a set of models often produces a better fit than any single model in the set (Garratt, Koop, Mise, and Vahey (2007), Marcellino, Stock, and Watson (2006), Rapach and Strauss (2007), and many others). In addition, anecdotal evidence shows that all central banks construct a variety of models, each of which produces a unique forecast.[7] The forecasts are then combined (at least implicitly) into a single number, based on subjective probabilities assigned to each model by banks' officials.

The models examined are:

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 root mean square prediction error (RMSPE) of Greenbook and random walk forecasts of inflation, and find them to be very similar.

2. *Iterated autoregression (IAR).* Another standard benchmark model is an 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.[8,9]

3. *Direct forecast from autoregression (DAR).* This model is closely related to the IAR model. However, 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.

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

[8] For "diagonals" and "first releases" models, p is set to 4, and for the "vintages" specification, I fix $p = 8$ since it appears to perform better. The same setup is used for the other autoregressive models described below, unless otherwise noted.

[9] Formally, *iterative* autoregressive model forecasts for long horizons cannot be justified for the case of "diagonals" data, as vintages $t-1$ and t would come from different data generating processes (DGPs). This problem does not exist for "first releases" and "vintages" data.

4. *ARMA(1, 1).* This framework models inflation as the sum of expected inflation and noise, and fits the rational expectation framework: $\pi_t = \rho_0 + \rho_1 \pi_{t-1} + \psi_1 \varepsilon_{t-1} + \varepsilon_t$. The empirical motivation 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 term-structure models.

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. Branch and Evans show that the specification with common constant gain γ significantly outperforms more complicated alternatives and also provides the best fit with the Survey of Professional Forecasters data. I consider CG-VAR with 4 different values of gain $\gamma = \{0.025, 0.050, 0.075, 0.100\}$.

6. *The 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:[10] $\pi_{t+h}^i = \rho_0 + \sum_{j=1}^{p_i^\pi} \rho_j \pi_{t-j} + \sum_{j=1}^{p_i^g} \delta_j g_{t-j}^y + \varepsilon_{it}$. In contrast to their specification, 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 $\{p_i^\pi, p_i^g\} \in \{1, \ldots, p\}$, and then average the forecasts using Bayesian model averaging (BMA). 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. Specifically, I employ approximate BMA, used in Garratt, Koop, Mise, and Vahey (2007).

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' MSPEs. The resulting forecast is the weighted average of individual forecasts of the models from the first cluster. Following Rapach and Strauss (2007), I use the $C(K, PB)$ algorithm to average individual forecasts with the number of clusters K equal to 5.[11] The crucial

[10] Van Norden (1995) shows that 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.

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. The battery of models may be 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^{π}_i, p^g_i are allowed to vary between $\{1, \ldots, 4\}$, and J_i takes values from $J_j = 0$ (no x_j variable is included in the model), to $J_j = n$ (all x_j variables are present).

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 (2009): $\pi^i_{t+h} = \rho_0 + \sum_{j=1}^{p} \rho_j \pi_{t-j} + \beta_i x_{it} + \varepsilon_{it}$, where $h = \{0, \ldots, 5\}$ 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 considerably better than 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.

Two different real-time datasets for the United States are employed. The first comes from the Federal Reserve Bank of Philadelphia, and it is described in detail in Croushore and Stark (2001).[12] From the Core Variables/Quarterly Observations/Quarterly Vintages subset, I extracted real and nominal GNP/GDP and the unemployment rate. The vintages go back to 1965:Q4, and 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. For example, 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.[13]

[11] Cluster size was determined first by splitting the sample into 2 parts, and for different values of $K = \{2, 3, 4, 5, 6\}$, the model was calibrated based on its performance over the first part of the sample. It was then tested using the second part of the sample, and $K = 5$ performed the best.

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

The Greenbook dataset, which is currently available up to 2001:Q4 (as of October, 2007), is also used.[14] From this dataset, I extract the annualized quarter-over-quarter growth rate forecast of the GNP/GDP price level, which is transformed into year-over-year growth rates by averaging 4 consequent inflation forecasts (some of which are actual realized values).[15] This series and other Taylor Rule variables are plotted in Fig. 1b and Fig. 1c.

4.2 Canadian dataset 1977:3–2007:1.

The real-time quarterly Canadian dataset is constructed from the January, April, July, and October issues of the *Bank of Canada Review*,[16] because new updated GDP data was typically released for the first time in these months. The first vintage in the dataset comes from the July 1977 issue 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/M1-Gross growth rate, the unemployment rate, CPI all items, and Core CPI.[17] 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 in January 1988 the latest real GDP value was for 1987:3.

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 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:Q4, but typically only 5–8 observations are recorded (the earliest being 1972:4). Finally, money growth vintages begin in 1974:Q1, and the earliest observation is 1970:1. The official money growth targets series was

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

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

[15] 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 $t-1$.

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

[17] Over time, this measure changes from CPI All Items minus Food to CPI All Items minus Food and Energy to Core CPI.

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.[18] The last recorded vintage in this dataset is March 2002, and for most major revisions, long historical time series going back to 1955:1 are recorded. I manually 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. Two other measures include the Sign statistic, 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. Surprisingly, despite its popularity, the Hodrick-Prescott detrending method is one of the worst at predicting the Greenbook estimates: besides having high RMSPE of 5.438, it produces a gap of the same sign as the Greenbook only in slightly more than 50% of

[18] Due to data availability, July 1992, October 1992 and January 1993 vintages were employed 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 two reasons why I do not use earlier data. First, neither of the monthly real GDP vintages of interest are available before September, 1983. Second, the data from the October 1981–July 1982 vintages is missing.

cases, and it is virtually uncorrelated with the Greenbook series. The worst performing model is the BN decomposition, although this result is expected: BN 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.[19]

5.2 Inflation forecasting results.

The results, which summarize the relative ability of the forecasting models to replicate Greenbook conditional forecasts, are presented in Table 2. We see that averaging typically gives us the smallest RMSPE (models (6) and (7)), and that the "vintages" 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. The "BMA Phillips curve" model (6) with "vintages" data has the most stable performance among all the models I consider. For the rest of the paper, it is the main specification used to construct inflation forecasts, as it appears to be the best model to replicate the Greenbook conditional forecasts of U.S. inflation.[20,21,22]

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.

[19] To test the robustness of this model to transferability outside the U.S., I compare its estimates of the German output gap to the official Bundesbank real-time output gap series. I restricted my consideration to the post-reunification subsample (1990:4–1999:4). Both the sign test and correlation are significant at 1 percent, and equal to 4.60 and 0.82, respectively.

[20] Using the multivariate model clustering instead leaves the main results of the paper unchanged.

[21] Anecdotal evidence suggests that the Greenbook contains *conditional* forecasts of the economy at some periods, and *unconditional* at others, which raises a question of stability of the forecasting model. However, data shows that even if this is indeed the case, the difference 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, and RMSPE picks the same "vintages" BMA Phillips curve model as the best model to replicate Greenbook forecasts.

[22] I also investigate whether the model that best predicts the *Greenbook* forecasts is also the model that best predicts *actual* inflation, and I find that the answer is no. In fact, using "diagonals" and "first-release," rarely used by the majority of researchers, typically produces smaller RMSPE than using "vintages."

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 new Federal Reserve Board Chairman Paul Volcker, who reduced inflation rates in 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 to 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, 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 the critique above.

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 always be higher than one, and its point estimate 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 statistically 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.

A first step in the analysis is to verify 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.[23,24] The sample spans the years 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 $h = \{0, \ldots, 6\}$, 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.

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 slightly, indicating that the forward-looking version of the Taylor rule might fit data better than the backward-looking one. 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 for $h = 0$ exceeds that for $h = 5$, indicating that smoothing does occur, but to a smaller extent than we would conclude by estimating the backward-looking version of the Taylor rule.[25]

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).[26] Besides including the standard Taylor rule variables (inflation and the output gap) I also include the output gap growth variable.

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. The point estimates, though, are slightly higher in the earlier subperiod. Second, we see that interest rate smoothing increased

---

[23] This involves estimation using generated regressors, which might cause estimates to be inefficient but unbiased (Pagan (1984)). However, to my knowledge, no variance-covariance matrix correction has been derived for the BMA case.

[24] To test the validity of inflation forecasts, I have compared Taylor rule estimates with artificial and original Greenbook projections over the available Greenbook sample. The difference between them is never statistically significant. The results also show that using realized values of inflation in place of real-time forecasts might result in biased estimates.

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

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

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. 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 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).[27] 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."

Despite significant achievements in controlling inflation, Canada did not experience the stable economic growth and high 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. He 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

[27] Estimation results over a 1991:1–2007:1 sample using various measures of the output gap are qualitatively similar to the 1998:1–2007:1 results (below).

positive and significant, although these results are completely reversed for his 1995:1–2000:4 subsample. However, he uses revised data and considers a backward-looking version of the Taylor Rule, while most models currently used at the Bank of Canada in conducting 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 usually 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 calibrated rather then estimated 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 the policy variable.[28] The output gap is defined as deviation from a linear time trend over the last 20 years, and inflation is measured with the year-over-year growth in the Core CPI (Fig. 1d). To obtain inflation forecasts, π_{t+h}, I fit the "BMA Phillips curve" to each vintage of Canadian real-time data and compute forecasts as described in Section 3.2.[29] Because the first release of data usually lags by 4 months, 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

[28] This is the first month after the month to which the real-time dataset refers.

[29] The same procedure is later employed to obtain inflation forecasts for Germany and the U.K. and output gap estimates for the U.K. If instead of the "best" U.S. model we used the "2nd best" alternatives, quadratic detrending for the output gap and model clustering for inflation forecasting, the results would stay qualitatively the same.

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 estimated inflation coefficient exceeding 1, the 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 $h = 0$.

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. A similar result obtained by Curtis (2005) led the author to conclude that the negative output gap response might be the main reason for the "Great Canadian slump." However, if 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 statistically significant, regardless of the presence of interest rate smoothing. The results also show that the Bank of Canada took account of the behavior of the Fed during this sample period: in specification (3), $\beta = 0.72$, while $\phi = 0.82$.

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 claimed 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 this 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 were not available to the central bank's officials at the time they were making decisions. Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) estimate a completely real-time version of the 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 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. Fig. 1e plots the data.

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 are presented 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.

The 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 significant only at the 10% level, indicating that the Bundesbank ran a mostly independent monetary policy. The deviation of the money growth rate from the target level is never significant, supporting the findings of Clarida, Gali, and Gertler (1998) and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008). The target inflation rate, π^*, can be estimated as in the previous case under the assumption that ex-post $R^* = 3.11\%$. Using estimates from specification (3), this corresponds to $\pi^* = 2.17\%$.

5.6 U.K. Monetary policy.

5.6.1 History of monetary policy

I estimate 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), the primary aim of which was controlling inflation. The policy appeared credible, and as a result, inflation fell rapidly from 19.07% in 1980:1 to 4.98% in 1983:1. Although it spiked again in the late 1980s and early 1990s, it never reached the pre-MTFS level (Fig. 1f). 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 was then 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 inappropriate 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 acted 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 between 1979–1987. Indeed, both regimes promoted price stability and successfully restrained inflation, although empirical results for the post-1992 sample remain 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%. 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. Neither study, however, uses real-time data.

5.6.2 Taylor rule estimation (U.K.)

Following standard practice, I use the three month Treasury Bill rate as a proxy for the central bank policy variable. Year-over-year growth in the GDP deflator is the inflation measure, and the output gap is defined as the deviation from a linear time trend over the last 20 years. The results of forward-looking Taylor rule estimates are presented in Table 3. 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."[30] 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 $R^* = 3.55\%$.

One of the results obtained by Clarida, Gali, and Gertler (1998), that the Bank of England followed the Bundesbank's monetary policy, appears questionable. They include the German money market rate (MMR) when estimating the Taylor rule for the 1979–1990 sample, but there is evidence that the 1979–1987 and 1987–1990 subperiods might be very different and the Bank of England followed German monetary policy only during the latter period. Their regression over two subsamples is estimated, with results presented in Table 4. The most important outcome is that, indeed, when we (potentially incorrectly) include the 1987–1990 subsample in the estimation, we conclude that the impact of the 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 the 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 probably driven 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.

5.7 Robustness check.

One remaining question is how robust the above results are to the choice of different inflation forecasting and output gap estimation techniques. In order to check that, I perform the following exercise. First, using the results from Tables 1 and 2, I pick and rank $m = \{1..6\}$ output gap measures and $n = \{1..6\}$ inflation forecasting techniques, with "1" being the "best" performing model, currently used in the paper to construct artificial "Greenbooks" for Canada, Germany, and the U.K. Then, for each country separately, I use the Wald test to compare the estimates of inflation, β, and output gap, γ, coefficients of the forward-looking Taylor rule from the "benchmark" $\{1, 1\}$ combination to point estimates from all possible pairs $\{n, m\}$ of models.[31]

[30] Note, however, that their estimate is significantly different from zero, while my estimate is not.

The corresponding p-values are presented in Table 6.

We can see that the results remain consistent even if the Bundesbank, the Bank of Canada, and the Bank of England do not employ the "best" U.S. models, but instead use other reasonable alternatives. In particular, there is slightly more latitude in choosing the inflation forecasting technique than choosing the output gap estimation method: with "rolling window," "quadratic," and (with some reservations) "linear" detrending, most of inflation forecasting techniques could be used, with the exception of the "random walk" model. However, this does not mean that the choice of the model can be completely arbitrary and thus is not really important: as either n or m or both increase, the estimates diverge, and the difference between them becomes significant.

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. The availability of real-time data is extremely important for both countries outside the United States, where central banks do not regularly release their forecasts to the public, and for the U.S., where forecasts are released with a five-year lag.

In order to estimate a central bank's real-time interest rate reaction function, it is important 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 rolling window linear 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 models in inflation and the GDP growth rate. Other aggregate methods also typically produce forecasts superior to single model projections. These forecasts are used to estimate forward-looking Taylor rules in the absence of forward-looking data, allowing us to extend the analysis beyond the U.S.

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

[31] Note that there is no need to do this for the U.S., as we already know that $\{1, 1\}$ works best for the United States. In addition, in the case of Germany, there is no uncertainty about the output gap measure as official central bank estimates of the output gap are available.

United States and German central banks respond more aggressively to one-year-ahead inflation forecasts, United Kingdom and Canadian reaction functions achieve maximum inflation response at the middle-term of roughly two quarters hence.

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 the availability of data for a small number of variables. With further development of real-time data, this research could 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 existing datasets become wider. For instance, for each country under consideration, the forecasting models could be tailored to account for variables that are known to be of interest to local central bankers, even though these variables might be of little importance for the Fed.

7 References

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*

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*

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*

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*

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. 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*

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. and Wright, J., 2009. Comparing Greenbook and reduced form forecasts using large realtime dataset. *Journal of Business and Economic Statistics, American Statistical Association, vol. 27(4), pages 468-479*

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., 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.*

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*

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

Molodtsova, T., Nikolsko-Rzhevskyy, A. and Papell, D., 2008. Taylor Rules and Real-Time Data: A Tale of Two Countries and One Exchange Rate. *Journal of Monetary Economics 55, S63-S79*

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*

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*

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*

Pagan, A., 1984. Econometric issues in the analysis of regressions with generated regressors. *International Economic Review, 25(1), 221-247*

Rapach D. and Strauss, J. 2007. Forecasting real housing price growth in eight district states. *Regional Economic Development, Federal Reserve Bank of St. Louis, issue Nov, pages 33-42*

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

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*

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 (Linear)			
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 ("vintages"). 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	BMA Phillips Curve	Cluste-ring	Data-rich BMA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Vintages								
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-releases								
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. DAR and IAR stay for direct and 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 (2009). "Vintages," "Diagonals," and "First releases" are all types of real-time data, which uses only information available to forecasters at the time they were making forecasts. Refer to Section 3 for further details.

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: The table presents 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 the "vintages" 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 the linear trend over the last 20 years. The output gap for Germany is the official Bundesbank series. Inflation is GDP deflator inflation for the US, UK, and Germany, and Core CPI inflation for Canada. Square brackets mark the "nowcast" of inflation (quarter t forecast as available at quarter t).

Table 4: U.S. and U.K. 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			1987:2–2007:1		
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
	Including			Excluding		
Panel B. U.K. full sample	1987:2–1990:3			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: The table presents NLLS estimates of $i_t = \rho i_{t-1} + (1-\rho)\{c + \beta E\pi_{t-1+h} + \gamma\widehat{y}_{t-1} + \lambda\triangle\widehat{y}_{t+3} + \phi r^{GR} + \xi de_t\} + \varepsilon_t$. Newey-West HAC standard errors are in parentheses. Inflation forecasts are obtained using the BMA Phillips curve model applied to the "vintages" data. See Section 5.2 for details. The forecast horizon h is equal to 5 for the U.S. and 3 for the U.K. The interest rate i_t is the Federal Funds Rate for the US, and 3 month TB rate for the UK. The output gap growth rate comes from two sources: the Greenbook series before 1997:4, taken from Orphanides (2003), is combined with the OECD estimates, which are calculated using the semi-annual issues of OECD *Economic Outlook*. I obtain quarterly values from annual estimates using quadratic interpolation. $de_t = 100\ln(e_t/e_{t-1})$ and e_t is the DM/GBP nominal exchange rate, constructed as the quarterly growth rate of DM/GBP nominal exchange rate before 1999:1, and EUR/GBP after that; the conversion rate is 1.93DM = 0.69GBP = 1.00EUR. The output gap is defined as deviations from the linear 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	1.04	0.54	3.07	2.50	2.40
	(0.41)	(0.52)	(1.20)	(1.02)	(0.97)
Output gap γ	0.21	0.32	0.86	1.26	1.23
	(0.09)	(0.09)	(0.48)	(0.72)	(0.68)
Money growth rate		-0.08		0.18	
		(0.17)		(0.32)	
Real DM/USD rate ζ				0.08	0.08
				(0.07)	(0.06)
Federal Funds Rate ϕ		0.27			
		(0.15)			
Smoothing ρ			0.91	0.90	0.89
			(0.04)	(0.04)	(0.04)
Const c	3.57	3.15	-0.67	-5.28	-4.47
	(1.60)	(1.63)	(3.25)	(4.39)	(4.39)
R^2	0.24	0.39	0.95	0.95	0.95

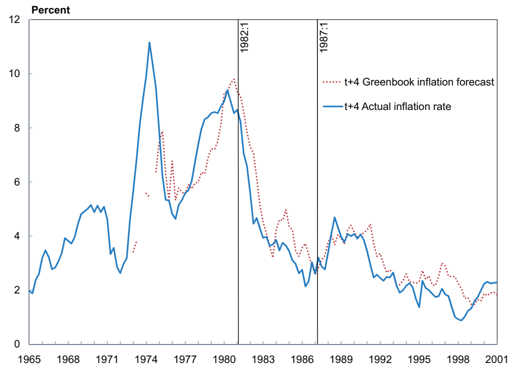
Notes: The table presents NLLS estimates of $i_t = \rho i_{t-1} + (1-\rho)\{c + \beta E\pi_{t-1+h} + \gamma\widehat{y}_{t-1} + \phi r_t^{US} + \xi de_t + \zeta E_t\} + \varepsilon_t$, where $de_t = 100\ln(e_t/e_{t-1})$ and e_t is the CAD/USD nominal exchange rate. E_t is the DM/USD real exchange rate, 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 the "vintages" data. See Section 5.2 for details. The forecast horizon h is equal to 4 for Canada and 6 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 the linear 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.

Table 6: p-values of the Wald test of no difference between the inflation, β, and output gap, γ, coefficients from the $\{1,1\}$ model and their point estimates from an $\{n,m\}$ model

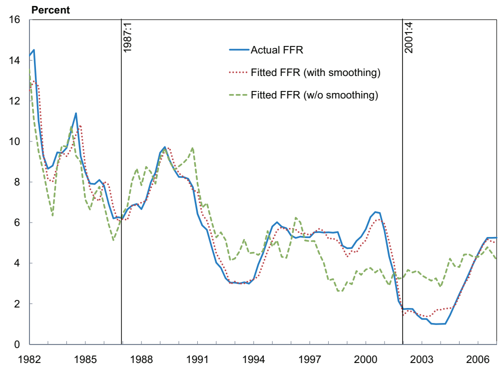
		Inflation forecasting model, n					
		BMA Phillips Curve	Cluste-ring	DAR(p)	IAR(p)	ARIMA (1,1)	RW
Output gap estimation model, m	Model rank $\{n,m\}$	1	2	3	4	5	6
Panel A: Canada							
Rolling Window (Linear)	1	1.00	0.99	0.48	0.28	0.20	0.04
Quadratic	2	0.99	0.99	0.46	0.26	0.17	0.03
Linear	3	0.92	0.97	0.25	0.13	0.03	0.00
Band Pass filter	4	0.00	0.02	0.00	0.00	0.00	0.00
Hodrick-Prescott $\lambda = 1600$	5	0.00	0.01	0.00	0.00	0.00	0.00
Beveridge-Nelson	6	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: U.K.							
Rolling Window (Linear)	1	1.00	0.93	0.63	0.71	0.67	0.40
Quadratic	2	0.99	0.91	0.58	0.60	0.51	0.33
Linear	3	0.61	0.64	0.66	0.42	0.59	0.08
Band Pass filter	4	0.28	0.00	0.00	0.00	0.00	0.00
Hodrick-Prescott $\lambda = 1600$	5	0.00	0.00	0.00	0.00	0.00	0.00
Beveridge-Nelson	6	0.00	0.00	0.00	0.00	0.00	0.00
Panel C: Germany							
Official Bundesbank Estimates	1	1.00	0.97	0.96	0.97	0.81	0.39

Notes: Models are sorted according to their performance, documented in Tables 1 and 2, with "1" denoting the most successful model in replicating the U.S. Greenbook. β and γ are the inflation and output gap coefficients estimates from a forward-looking Taylor rule with the forecast horizon h corresponding to Tables 4 and 5. For the "Rolling Window (Linear)" detrending, the window size is 80 quarters. For the Band Pass and Hodrick-Prescott filters, the "Extended by $K = 12$" and "Original" specifications are used, respectively. Inflation forecasts are obtained using the "vintages" data. For Germany, there is no uncertainty about the output gap measure as the official Bundesbank estimates of the output gap are available.

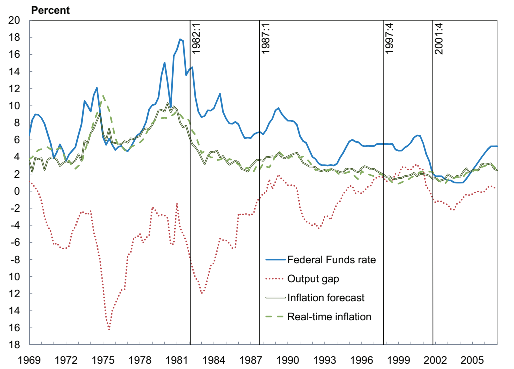
Figure 1: Monetary policy determinants



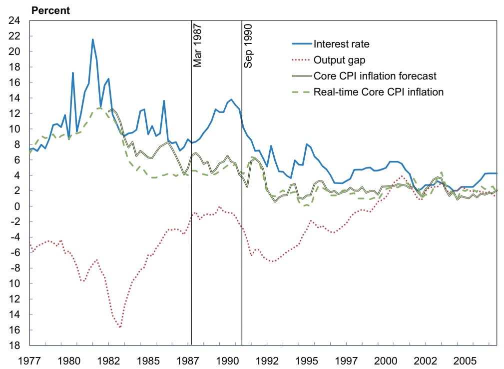
a. Greenbook forecast and actual inflation t+4 periods ahead



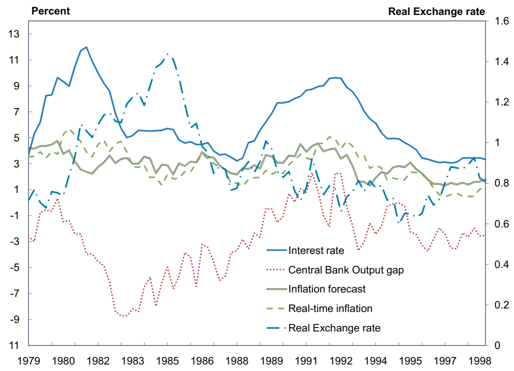
b. Actual and fitted Federal Funds rate



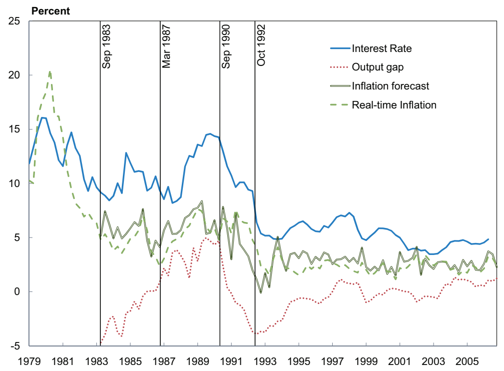
c. U.S.



d. Canada



e. Germany



f. U.K.

Notes: The inflation forecast horizon is one year for the U.S. and Germany, and six months for Canada and the UK. Inflation is GDP deflator inflation for the U.K. and Germany, and Core CPI inflation for Canada. For Canada and the U.K., the output gap is defined as deviations from the linear trend over the last 20 years; for Germany, the output gap is the official Bundesbank series. Due to unavailability of real-time U.K. inflation data prior to 1983:3, revised inflation is shown for that subperiod.