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ABSTRACT

A Century of Inflation Forecasts*

We investigate inflation predictability in the United States across the monetary regimes of the XXth century. The forecasts based on money growth and output growth were significantly more accurate than the forecasts based on past inflation only during the regimes associated with neither a clear nominal anchor nor a credible commitment to fight inflation. These include the years from the outbreak of World War II in 1939 to the implementation of the Bretton Woods Agreements in 1951, and from Nixon's closure of the gold window in 1971 to the end of Volcker's disinflation in 1983.

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1 Introduction

Monetary authorities across the world have always devoted a large amount of resources to forecast inflation. The history of monetary policy, however, suggests that the entrepreneurship of predicting changes in the price level has had mixed success over time. In some periods, inflation appears predictable in that multivariate models produce forecasts that are more accurate than the forecasts based on naïve models. In other periods, virtually no model seems to improve upon either an autoregressive process or the unconditional mean of inflation (see for instance Stock and Watson, 2007 and 2008).

In this paper, we use a century of quarterly and annual observations for the United States to ask whether the conduct of monetary policy affects the ability of a simple multivariate model to predict inflation. The U.S. monetary history of the XX^{th} century reveals that the monetary regimes characterized by either a clear nominal anchor or a credible anti-inflationary policy stance has been associated with lower levels of inflation (see Bordo and Schwartz, 1999). Our goal is to investigate whether in these regimes inflation has become harder to forecast using either money growth, as suggested by the quantity theory, or output growth, as suggested by a Phillips curve relationship.[1]

We perform a historical evaluation of inflation forecasts across monetary regimes using a flexible statistical model that features drifting coefficients and stochastic volatility. The time-variation is important because it will allow us to identify *endogenously* the dates of any possible change in predictability, and therefore to assess whether these dates correspond to major changes in the conduct of monetary policy. Our main result is that money growth and output growth had marginal predictive power for inflation only during times in which, according to the narrative account of the U.S. monetary history, the monetary authorities did not succeed to establish a clear nominal anchor or an inflation fighter reputation.

The paper is organized as follows. Section 2 describes our time-varying forecasting models as well as the time-varying benchmark specification. Section 3 defines the monetary regimes and presents the main results. A sensitivity analysis is offered in Section 4 before conclusions. The Appendix reports estimation details.

[1] Using a small-scale sticky price DSGE model, Benati and Surico (2008) show that inflation predictability is inversely related to the degree of policy activism in the interest rate response to inflation.

2 The statistical model

In this section, we describe the forecasting model, which we will then use in section 3 to investigate the accuracy of the inflation forecasts across monetary regimes. The forecasting model is a Vector Auto Regression (VAR) in which both the autoregressive coefficients and the elements of the innovation covariance matrix are allowed, but not required, to drift over time. The reason for using a time-varying statistical model is twofold. First, the dynamics and volatilities of money growth, inflation and output growth have exhibited substantial instabilities over the XX^{th} century (see Sargent and Surico, 2010). Second, our long sample cuts across two World Wars, the great depression, the great inflation and several monetary regimes which differed markedly in their success to establish a credible framework to gain control over inflation.

2.1 A VAR with drifting coefficients and stochastic volatility

The vector of endogenous variables is denoted by $y_t = [\pi_t, z_t]'$ where π_t is the the variable to be predicted, the inflation rate, and z_t is the predictor, either money growth, Δm_t, or real GDP growth, Δx_t. We assume that y_t admits the following VAR representation:

$$y_t = A_{0,t} + A_{1,t}y_{t-1} + ... + A_{p,t}y_{t-p} + \varepsilon_t \tag{1}$$

where $A_{0,t}$ is a vector of time-varying intercepts, $A_{i,t}$ are matrices of time-varying coefficients, $i = 1, ..., p$ and ε_t is a Gaussian white noise with zero mean and time-varying covariance matrix Σ_t. Let $A_t \equiv [A_{0,t}|A_{1,t}..., A_{p,t}]$, and $\theta_t \equiv vec(A_t')$, where $vec(\cdot)$ is the column stacking operator. The VAR time-varying parameters, collected in the vector θ_t, are postulated to evolve according to:

$$p(\theta_t \mid \theta_{t-1}, Q) = I(\theta_t)\ f(\theta_t \mid \theta_{t-1}, Q) \tag{2}$$

where $I(\theta_t)$ is an indicator function that takes a value of 0 when the roots of the associated VAR polynomial are inside the unit circle and is equal to 1 otherwise. $f(\theta_t \mid \theta_{t-1}, Q)$ is given by:

$$\theta_t = \theta_{t-1} + \omega_t \tag{3}$$

where ω_t is a Gaussian white noise with zero mean and covariance Ω.

The VAR reduced-form innovations in (1) are postulated to be zero-mean normally distributed, with time-varying covariance matrix Σ_t that is factored as:

$$\Sigma_t = F_t D_t F_t'$$

where F_t is lower triangular, with ones on the main diagonal, and D_t a diagonal matrix. Let σ_t be the vector of the diagonal elements of $D_t^{1/2}$ and ϕ_t the off-diagonal element of the matrix F_t^{-1}. We postulate that the standard deviations, σ_t, evolve as geometric random walks, belonging to the class of models known as stochastic volatility. The contemporaneous relationship ϕ_t among the two variables of the VAR is assumed to evolve as an independent random walk, leading to the following specifications:

$$\begin{aligned} \log \sigma_t &= \log \sigma_{t-1} + \xi_t && (4) \\ \phi_t &= \phi_{t-1} + \psi_t && (5) \end{aligned}$$

where ξ_t and ψ_t are Gaussian white noises with zero mean and covariance matrix Ξ and Ψ. We postulate that that ξ_t, ψ_t, ω_t, ε_t are mutually uncorrelated at all leads and lags.

2.2 Estimation and priors specification

The model (1)-(4) is estimated using Bayesian methods. A detailed description of the algorithm, including the Markov-Chain Monte Carlo (MCMC) used to simulate the posterior distribution of the hyperparameters and the states conditional on the data, is provided in the Appendix and it can also be found in D'Agostino, Gambetti and Giannone (2009).

It is worth emphasizing that the algorithm used in this paper takes explicitly into account the uncertainty surrounding the estimates of the drifting coefficients. Although we are unable to characterize analytically the posterior density of the statistics of interest, subject to regularity conditions described in Gelman et al. (1995), the successive draws of the Markov-chain converge to an invariant density that equals the desired posterior density. This implies that the MCMC algorithm allow us to compute error bands around the median estimates of our measure of predictability, thereby providing a very natural way to assess the statistical significance of any possible change in forecast accuracy.

As for the specification of the priors, we follow Primiceri (2005) and assume that the priors for the initial states θ_0 of the time varying coefficients, the simultaneous relationship

ϕ_0 and log standard errors $\log\sigma$ are normally distributed. The priors for the hyperparameters, Ω, Ξ and Ψ are assumed to be distributed as independent inverse-Wishart. More specifically, we have the following priors.

- Time varying coefficients: $P(\theta_0) \sim N(\hat{\theta}, \hat{V}_\theta)$ and $P(\Omega) \sim IW(\Omega_0^{-1}, \rho_1)$.
- Stochastic volatilities: $P(\log\sigma_0) \sim N(\log\hat{\sigma}, I_n)$ and $P(\Psi_i) \sim IW(\Psi_{0i}^{-1}, \rho_{2i})$.
- Simultaneous relationship: $P(\phi_0) \sim N(\hat{\phi}, \hat{V}_\phi)$ and $P(\Xi) \sim IW(\Xi_0^{-1}, \rho_3)$; where the scale matrices are parametrized as $\Omega_0^{-1} = \lambda_1\rho_1\hat{V}_\theta$, $\Psi_{0i} = \lambda_{2i}\rho_{2i}\hat{V}_{\phi_i}$ and $\Xi_0 = \lambda_3\rho_3 I_n$.

The hyper-parameters are calibrated using a time invariant recursive VAR estimated using a pre-sample of size T_0, corresponding to the first 32 quarters. For the initial states θ_0 and the contemporaneous relationship ϕ_0, we set the means, $\hat{\theta}$ and $\hat{\phi}_i$, and the variances, $\hat{V}_\theta$ and $\hat{V}_{\phi_i}$, to be the maximum likelihood point estimates and four times its variance. For the initial states of the log volatilities, $\log\sigma_0$, the mean of the distribution is chosen to be the logarithm of the point estimates of the standard errors of the residuals of the estimated time invariant VAR.

The degrees of freedom for the covariance matrix of the innovations to the drifting coefficients, ρ_1, are set equal to T_0, the size of the pre-sample. The degrees of freedom for the priors on the variances of the innovations to the stochastic volatilities, ρ_{2i}, and to the simultaneous relationship, ρ_3, are set to the minimum necessary to guarantee a proper prior, namely the number of rows in Ξ_0^{-1} and Ψ_{0i}^{-1} plus one, respectively. Following the empirical literature, we choose conservative priors for the parameters governing the amount of time-variation in the unobserved states: $\lambda_1 = \lambda_2 = 10e$-04 and $\lambda_3 = .001$.[2]

2.3 Forecasts

The statistical model described in equation (1) has the following companion form:

$$\mathbf{y}_t = \boldsymbol{\mu}_t + \mathbf{A}_t\mathbf{y}_{t-1} + \epsilon_t$$

with $\mathbf{y}_t \equiv [y_t'...y_{t-p+1}']'$, $\epsilon_t \equiv [\varepsilon_t' 0...0]'$ and $\boldsymbol{\mu}_t \equiv [A_{0,t}' 0...0]'$ are $np \times 1$ vectors and

$$\mathbf{A}_t = \begin{pmatrix} & A_t & \\ I_{n(p-1)} & & 0_{n(p-1),n} \end{pmatrix}$$

[2]The results below are robust to setting the $\lambda' s$ to values ten times larger. Stock and Watson (1996) show that models with a lesser conservative degree of a priori time variation perform poorly in forecasting.

where $A_t \equiv [A_{1,t}...A_{p,t}]$ is an $n \times np$ matrix, $I_{n(p-1)}$ is an $n(p-1) \times n(p-1)$ identity matrix and $0_{n(p-1),n}$ is a $n(p-1) \times n$ matrix of zeros. Let $\hat{\boldsymbol{\mu}}_t$ and $\hat{\mathbf{A}}_t$ denote the median of the joint posterior distribution for $\hat{\boldsymbol{\mu}}_t$ and $\hat{\mathbf{A}}_t$ (see appendix for the details). The one step ahead forecast of the endogenous variables is denoted by $\mathbf{y}_{t+1}$ and it is given by:

$$\hat{\mathbf{y}}_{t+1|t} = \hat{\boldsymbol{\mu}}_t + \hat{\mathbf{A}}_t \mathbf{y}_t \tag{6}$$

The forecasts $h-$step ahead are computed iteratively:

$$\hat{\mathbf{y}}_{t+h|t} = \hat{\boldsymbol{\mu}}_t + \hat{\mathbf{A}}_t \hat{\mathbf{y}}_{t+h-1} = \sum_{j=1}^{h} \hat{\mathbf{A}}_t^{j-1} \hat{\boldsymbol{\mu}}_t + \hat{\mathbf{A}}_t^h \mathbf{y}_t \tag{7}$$

Ideally, when computing multi-step forecasts, one should also account for the fact that the parameters drift going forward from date t. But this is computationally challenging because it requires integrating a high-dimensional predictive density across all possible paths of future parameters. Consistent with a long-standing tradition in the learning literature (referred to as 'anticipated-utility' by Kreps, 1998), we instead update the elements of $\hat{\boldsymbol{\mu}}_t$ and $\hat{\mathbf{A}}_t$ period-by-period and then treat the updated values as if they would remain constant going forward in time.

Our objective is to predict the h-period log change in prices $\pi_{t+h}^h = \frac{400}{h} log(\frac{P_{t+h}}{P_t})$, where P_{t+h} is the GDP deflator at time $t+h$ and $\frac{400}{h}$ is the normalization term. The forecasts based on the *bivariate autoregressive* model with drifting coefficients and stochastic volatility are compared with the forecasts based on the *univariate autoregressive* model with drifting coefficient and stochastic volatility. For both specifications, we keep the same lag order, $p = 2$, and the same prior beliefs.

Forecast accuracy is evaluated using the Smoothed Mean Square Forecast Error (SMSFE). For each Gibbs sampling repetition, we compute the squared forecast errors over the whole sample, and then we smooth it taking means over a rolling window of 31 quarters. The SMSFE is a measure of the average forecast accuracy over the time window. To facilitate comparisons between the time-varying VAR and the benchmark model, we report results in terms of their *relative* SMSFE, which is the *ratio* of the SMSFE from the time-varying VAR over the SMSFE from the benchmark model. Values of the relative SMSFE below one indicate that the forecasts produced by the VAR are, on average, more accurate that the forecasts produced by the univariate model.

To assess the statistical significance of any possible improvement (or deterioration) in predictability, we report median values and the central 68% posterior error bands associated with the distribution of the relative SMSFE across Gibbs sampling repetitions. If the value of one falls outside the error bands, then the two models generate forecasts that are statistically different one from the other.

3 Inflation predictability across monetary regimes

We fit two time-varying VARs in inflation and money growth, and inflation and output growth on U.S. quarterly data constructed as the log differences of GDP deflator, real GDP and M2 stock. As for the benchmark model, we fit a time-varying univariate process for inflation. The full sample is 1875Q1-2007Q4. We use data until 1883Q3 to calibrate the priors. The first estimation sample is 1883Q4-1899Q4. The first one step ahead forecast refers then to 1900Q1. The series for GDP deflator and real GDP (M2) are available from the FRED database since 1947Q1 (1959Q1). Prior to that, we apply backward the growth rates on the GNP deflator, real GNP and M2 series reported by Balke and Gordon (1986). The estimates of the time-varying VAR and the time-varying AR models are then used to construct the measure of relative predictability SMSFE described in section 2.3.

Before proceeding, a word of caution is warranted about the interpretation of our results over the pre-WWII period where the historical annual data have been interpolated by Balke and Gordon (1986) to produce quarterly observations. To assess the extent to which such an interpolation may affect our results, in section 4 we present forecasts based on annual data. The findings on annual data confirm the findings in this section.

3.1 Monetary regimes

Our analysis intends to assess the evidence on the evolution of inflation predictability from the statistical models against the evidence on the evolution of monetary policy from the narrative account of the U.S. economic history. To this end, in this section we report the dates for some major changes in monetary regimes. These dates will be used to locate vertical axes on the charts for the evolution of the relative SMSFE. Following Meltzer (1986), we divide the U.S. monetary history of the XXth century in six major regimes:

1. From the beginning of the sample to 1931Q3: Gold standard. Ended when Britain left the gold standard.[3]

2. From 1931Q4 to 1939Q3: Mixed system. Ended with the outbreak of WWII.[4]

3. From 1939Q4 to 1951Q1: pegged interest rate for most of the period. Ended with the Treasury-Federal Reserve Accord which removed the obligation to support the U.S. government bonds market and thus allowed the Fed to pursue an independent monetary policy.

4. From 1951Q2 to 1971Q3: Bretton Woods. Ended when Nixon closed the gold window.

5. From 1971Q4 to 1983Q4: Great inflation. Ended with Volcker's disinflation.

6. From 1984Q1 to the end of the sample: Great moderation.

A similar categorization has been used by Bordo and Haubrich (2008) to investigate the evolution of the marginal predictive power of the yield spread for output growth.

3.2 The evolution of inflation predictability

In the top (bottom) panel of figure 1, we report the relative SMSFE between the forecasts produced by a bivariate VAR in inflation and money growth (inflation and output growth) and the forecasts produced by a univariate autoregressive process for inflation. Whenever one is inside the error bands of the relative SMSFE statistics, we conclude that money growth or output growth have no marginal predictive power for inflation over and above its past values. For the sake of exposition, figure 1 focuses on eight-quarter ahead forecasts which represents the typical horizon at which central banks are expected to meet their (implicit) target. Figure 2 reports results for the one, four and twelve quarters horizons. Vertical lines represent the monetary regime shifts discussed in section 3.1.

[3] Meltzer (1986) further divides this period into 'Gold standard without a central bank' up to 1914Q4 (marked as dotted line in the figures below) and 'Gold standard with a central bank' afterwards.

[4] The fourth quarter of 1941 is another plausible closing date for this period as it corresponds to the declaration of war to Germany and Japan. We prefer to draw a vertical line earlier, however, because during the period of U.S. neutrality large-scale orders for war materials, paid by large inflow of gold stock, resulted in a sharp rise in money growth. This, together with a greatly expanded defense program, led to a sustained increase in wholesale prices as the Fed undertook no extensive operations to offset the rapid rise in gold stock, money stock or prices (see Friedman and Schwartz, 1963, pp. 550-3).

Four main results emerge from figure 1. First, over the entire XXth century, inflation predictability appears the exception rather than the rule. Second, the forecasts produced by the bivariate model in inflation and money growth are significantly more accurate than the forecasts produced by the univariate model only during the years between the outbreak of WWII in 1939 and the Treasury-Federal Reserve accord in 1951.[5] Third, since the Federal funds rate have traded consistently above the discount rate in 1966,[6] output growth had marginal predictive power for inflation in only two periods: (i) the years that extend from the great inflation of the 1970s to the early 1980s when Volcker built the credibility for an anti-inflationary policy stance (see Goodfriend and King, 2005), and (ii) the years between 1997 and 2000 when the Fed leaned against the wind of the I.T. boom.[7] Fourth, under the Gold standard, the Bretton Woods system and most of the great moderation sample money growth and output growth had no marginal predictive power for inflation.

The left (right) column of figure 2 shows the relative SMSFE based on the VAR in inflation and money growth (inflation and output growth) for different horizons. The results as well as the dating of the changes in predictability are very similar to those in figure 1. During the Great Depression, however, money growth appears to have marginal predictive power for inflation at short horizons. In the period between the creation of the Federal Reserve System in 1914 and the exit of Britain from the gold standard in 1931, the forecasts four-quarters ahead based on money growth are significantly more accurate than the forecasts based on the univariate model.

It is worth emphasizing that during the Gold Standard the variance of inflation and the *absolute* SMSFEs associated with both the bivariate models and the univariate benchmark model were significantly larger than the variance and the absolute SMSFEs during the 1930s, the 1970s or the great moderation period. This is illustrated in figure 3 which reports the *absolute* SMSFE of the univariate model for inflation at eight-quarters horizon. Similar results are obtained at one, four and twelve quarter horizons. Altogether, this suggests that changes in predictability are not a mere reflection of changes in volatility.

[5] The deflation episodes associated with the 1931Q3-33Q1 and the 1937Q1-38Q1 recessions are likely to account for the poor performance of the forecasts based on money growth over the 1931Q4-1939Q3 period.

[6] This suggests that prior to 1966 the federal funds rate was not used as the primary policy instrument.

[7] Using a different statistical model over a post-WWII sample, Stock and Watson (2008) find similar results for the ability of output growth to forecast inflation.

4 Sensitivity analysis

In this section, we investigate further the performance of our forecasting models by presenting results for three additional exercises. First, we employ a time-varying *trivariate* VAR in money growth, inflation and output growth as alternative, augmented forecasting model. Second, we run the predictive analysis of the previous section using annual (rather than quarterly interpolated) observations. Third, we compare the forecasts based on our benchmark specification to the forecasts based on the unobserved components model with stochastic volatility proposed by Stock and Watson (2007).

4.1 Augmenting the VAR

Given the focus on marginal predictability, in Section 3 we have studied the out of sample performance of (*i*) a bivariate model in inflation and money growth and (*ii*) a bivariate model in inflation and output growth relative to a univariate specification for inflation. In this section, we wish to assess the extent to which the forecasts from a time-varying augmented VAR in inflation, money growth and output growth can improve upon the forecasts from a univariate time-varying autoregressive model. The results of this exercise are reported in figure 4 and they corroborate the findings in figures 1 and 2 at all horizons. In particular, the link between the conduct of monetary policy and the ability to forecast inflation is robust to using a trivariate specification.

Similar results, not reported but available upon request, are obtained increasing the lag order of the bivariate VARs to four over the post-WWII sample.

4.2 Annual data

As the pre-WWII quarterly data available in Balke and Gordon (1986) are interpolated, it is useful to check whether our results over this period are overturned by using annual observations. In figure 5, we report the relative SMSFEs based on estimated models which are the same as the estimated models behind figure 2 except for the frequency of the observations which is now annual. Accordingly, the forecast horizons are now one, two and three years. Figure 5 confirms by and large the findings based on quarterly observations reported in figure 2. Over the pre-WWII period, money growth and output growth had rarely predictive power for inflation. Furthermore, over the later sample, money growth helped predict inflation only in the pre-Bretton Woods regime while output growth was useful only during the 1970s great inflation. While the use of annual observations makes the uncertainty around the relative SMSFEs larger and the location of the vertical lines more imprecise, the evidence in figure 5 is still suggestive of a significant association between monetary policy regimes and inflation predictability.

4.3 An alternative time-varying univariate model

In an important contribution, Stock and Watson (2007) propose an Unobserved Components model with Stochastic Volatility (UCSV) for inflation. In this section, we are interested to compare the predictive accuracy of our univariate model with drifting coefficients and stochastic volatility to the predictive accuracy of the UCSV local-level model. Figure 6 shows the ratio of the SMSFEs at one, two and three years horizon between the Time-Varying AutoRegressive (TV-AR) and the UCSV specifications fitted on annual observations. Ratios below one imply that the forecasts of the UCSV are less accurate than the forecasts of the TV-AR. The evidence suggests that no specification performs systematically better than the other as the SMSFE ratio fluctuates around one in all three panels. At one-year (three-years) horizon, for instance, the forecasts of the UCSV model are more accurate than the forecasts of the TV-AR model 67% (55%) of the times. These numbers become 54% and 47% using quarterly observations.

5 Conclusions

This paper estimates Bayesian VARs with drifting coefficients and stochastic volatility to investigate the marginal predictive power of money growth and output growth for inflation across the U.S. monetary policy regimes of the XX^{th} century. Our main finding is that neither money growth nor output growth help forecast inflation during the regimes characterized by a clear nominal anchor such as the Gold Standard, Bretton Woods and the Great Moderation. During the 1970s great inflation (the pre-Bretton Woods period), in contrast, the forecasts based on a bivariate VAR with output growth (money growth) are more accurate than the forecasts based on a univariate autoregressive process. Our results are consistent with the notion that a policy regime which successfully stabilizes inflation makes it harder to improve upon the forecasts based on näive models.

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Appendix

Estimation is performed using Bayesian methods. To draw from the joint posterior distribution of model parameters we use a Gibbs sampling algorithm similar to the one described by Primiceri (2005). The idea behind the algorithm is to draw sets of coefficients from known conditional posterior distributions. The algorithm is initialized at some values and, under some regularity conditions, the draws converge to a draw from the joint posterior after a burn in period. Let z be a $(q \times 1)$ vector, and z^T denote the sequence $[z_1', ..., z_T']'$. Each repetition is then composed of the following steps, with s^T to be defined below:

1. $p(\sigma^T | x^T, \theta^T, \phi^T, \Omega, \Xi, \Psi, s^T)$
2. $p(s^T | x^T, \theta^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi)$
3. $p(\phi^T | x^T, \theta^T, \sigma^T, \Omega, \Xi, \Psi, s^T)$
4. $p(\theta^T | x^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi, s^T)$
5. $p(\Omega | x^T, \theta^T, \sigma^T, \phi^T, \Xi, \Psi, s^T)$
6. $p(\Xi | x^T, \theta^T, \sigma^T, \phi^T, \Omega, \Psi, s^T)$
7. $p(\Psi | x^T, \theta^T, \sigma^T, \phi^T, \Omega, \Xi, s^T)$

Gibbs sampling algorithm

• Step 1: sample from $p(\sigma^T | y^T, \theta^T, \phi^T, \Omega, \Xi, \Psi, s^T)$

To draw σ^T we use the algorithm of Kim, Shephard and Chibb (KSC) (1998). Consider the system of equations $y_t^* \equiv F_t^{-1}(y_t - X_t'\theta_t) = D_t^{1/2} u_t$, where $u_t \sim N(0, I)$, $X_t = (I_n \otimes x_t')$, and $x_t = [1_n, y_{t-1} ... y_{t-p}]$. Conditional on y^T, θ^T, and ϕ^T, y_t^* is observable. Squaring and taking the logarithm, we obtain

$$y_t^{**} = 2r_t + \upsilon_t \tag{8}$$

$$r_t = r_{t-1} + \xi_t \tag{9}$$

where $y_{i,t}^{**} = \log((y_{i,t}^*)^2 + 0.001)$ –the constant (0.001) is added to make estimation more robust– $\upsilon_{i,t} = \log(u_{i,t}^2)$ and $r_t = \log \sigma_{i,t}$. Since, the innovation in (8) is distributed as

$\log\chi^2(1)$, we use, following KSC, a mixture of 7 normal densities with component probabilities q_j, means $m_j - 1.2704$, and variances v_j^2 (j=1,...,7) to transform the system in a Gaussian one, where $\{q_j, m_j, v_j^2\}$ are chosen to match the moments of the $\log\chi^2(1)$ distribution. The values of the parameters are reported in table 1.

Table 1: ***Parameters Specification***

j	q_j	m_j	v_j^2
1.0000	0.0073	-10.1300	5.7960
2.0000	0.1056	-3.9728	2.6137
3.0000	0.0000	-8.5669	5.1795
4.0000	0.0440	2.7779	0.1674
5.0000	0.3400	0.6194	0.6401
6.0000	0.2457	1.7952	0.3402
7.0000	0.2575	-1.0882	1.2626

Let $s^T = [s_1, ..., s_T]'$ be a matrix of indicators selecting the member of the mixture to be used for each element of v_t at each point in time. Conditional on s^T, $(v_{i,t}|s_{i,t} = j) \sim N(m_j - 1.2704, v_j^2)$, we can use the algorithm of Primiceri (2005) to draw r_t (t=1,...,T) from $N(r_{t|t+1}, R_{t|t+1})$, where the mean $r_{t|t+1} = E(r_t|r_{t+1}, y^t, \theta^T, \phi^T, \Omega, \Xi, \Psi, s^T,)$ and the variance $R_{t|t+1} = Var(r_t|r_{t+1}, y^t, \theta^T, \phi^T, \Omega, \Xi, \Psi, s^T)$.

- Step 2: sample from $p(s^T|y^T, \theta^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi)$

Conditional on $y_{i,t}^{**}$ and r^T, we independently sample each $s_{i,t}$ from the discrete density defined by $Pr(s_{i,t} = j|y_{i,t}^{**}, r_{i,t}) \propto f_N(y_{i,t}^{**}|2r_{i,t} + m_j - 1.2704, v_j^2)$, where $f_N(y|\mu, \sigma^2)$ denotes a normal density with mean μ and variance σ^2.

- Step 3: sample from $p(\phi^T|y^T, \theta^T, \sigma^T, \Omega, \Xi, \Psi, s^T)$

Consider again the system of equations $F_t^{-1}(y_t - X_t'\theta_t) = F_t^{-1}\hat{y}_t = D_t^{1/2}u_t$. Conditional on θ^T, $\hat{y}_t$ is observable. Since F_t^{-1} is lower triangular with ones in the main diagonal, each equation in the above system can be written as

$$\hat{y}_{1,t} = \sigma_{1,t}u_{1,t} \tag{10}$$

$$\hat{y}_{i,t} = -\hat{y}_{[1,i-1],t}\phi_{i,t} + \sigma_{i,t}u_{i,t} \quad i = 2, ..., n \tag{11}$$

where $\sigma_{i,t}$ and $u_{i,t}$ are the i^{th} elements of σ_t and u_t respectively, $\hat{y}_{[1,i-1],t} = [\hat{y}_{1,t}, ..., \hat{y}_{i-1,t}]$.

Under the block diagonality of Ψ, the algorithm of Primiceri (2005) can be applied equation by equation, obtaining draws for $\phi_{i,t}$ from a $N(\phi_{i,t|t+1}, \Phi_{i,t|t+1})$, where $\phi_{i,t|t+1} = E(\phi_{i,t}|\phi_{i,t+1}, y^t, \theta^T, \sigma^T, \Omega, \Xi, \Psi)$ and $\Phi_{i,t|t+1} = Var(\phi_{i,t}|\phi_{i,t+1}, y^t, \theta^T, \sigma^T, \Omega, \Xi, \Psi)$.

- Step 4: sample from $p(\theta^T|y^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi, s^T)$

Conditional on all other parameters and the observables we have

$$y_t = X_t'\theta_t + \varepsilon_t \tag{12}$$

$$\theta_t = \theta_{t-1} + \omega_t \tag{13}$$

Draws for θ_t can be obtained from a $N(\theta_{t|t+1}, P_{t|t+1})$, where $\theta_{t|t+1} = E(\theta_t|\theta_{t+1}, y^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi)$ and $P_{t|t+1} = Var(\theta_t|\theta_{t+1}, y^T, \sigma^T, \phi^T, \Omega, \Xi, \Psi)$ are obtained with the algorithm of Primiceri (2005).

- Step 5: sample from $p(\Omega|y^T, \theta^T, \sigma^T, \phi^T, \Xi, \Psi, s^T)$

Conditional on the other coefficients and the data, Ω has an Inverse-Wishart posterior density with scale matrix $\Omega_1^{-1} = (\Omega_0 + \sum_{t=1}^T \Delta\theta_t(\Delta\theta_t)')^{-1}$ and degrees of freedom $df_{\Omega_1} = df_{\Omega_0} + T$, where Ω_0^{-1} is the prior scale matrix, df_{Ω_0} are the prior degrees of freedom and T is length of the sample use for estimation. To draw a realization for Ω, we make df_{Ω_1} independent draws z_i (i=1,...,df_{Ω_1}) from $N(0, \Omega_1^{-1})$ and compute $\Omega = (\sum_{i=1}^{df_{\Omega_1}} z_i z_i')^{-1}$ (see Gelman et. al., 1995).

- Step 6: sample from $p(\Xi_{i,i}|y^T, \theta^T, \sigma^T, \phi^T, \Omega, \Psi, s^T)$

Conditional to the other coefficients and the data, Ξ has an Inverse-Wishart posterior density with scale matrix $\Xi_1^{-1} = (\Xi_0 + \sum_{t=1}^T \Delta\log\sigma_t(\Delta\log\sigma_t)')^{-1}$ and degrees of freedom $df_{\Xi_1} = df_{\Xi_0} + T$ where Ξ_0^{-1} is the prior scale matrix and df_{Ξ_0} the prior degrees of freedom. Draws are obtained as in step 5.

- Step 7: sample from $p(\Psi|y^T, \theta^T, \sigma^T, \phi^T, \Omega, \Xi, s^T)$.

Conditional on the other coefficients and the data, Ψ_i has an Inverse-Wishart posterior density with scale matrix $\Psi_{i,1}^{-1} = (\Psi_{i,0} + \sum_{t=1}^T \Delta\phi_{i,t}(\Delta\phi_{i,t})')^{-1}$ and degrees of freedom $df_{\Psi_{i,1}} = df_{\Psi_{i,0}} + T$ where $\Psi_{i,0}^{-1}$ is the prior scale matrix and $df_{\Psi_{i,0}}$ the prior degrees of freedom. Draws are obtained as in step 5 for all i.

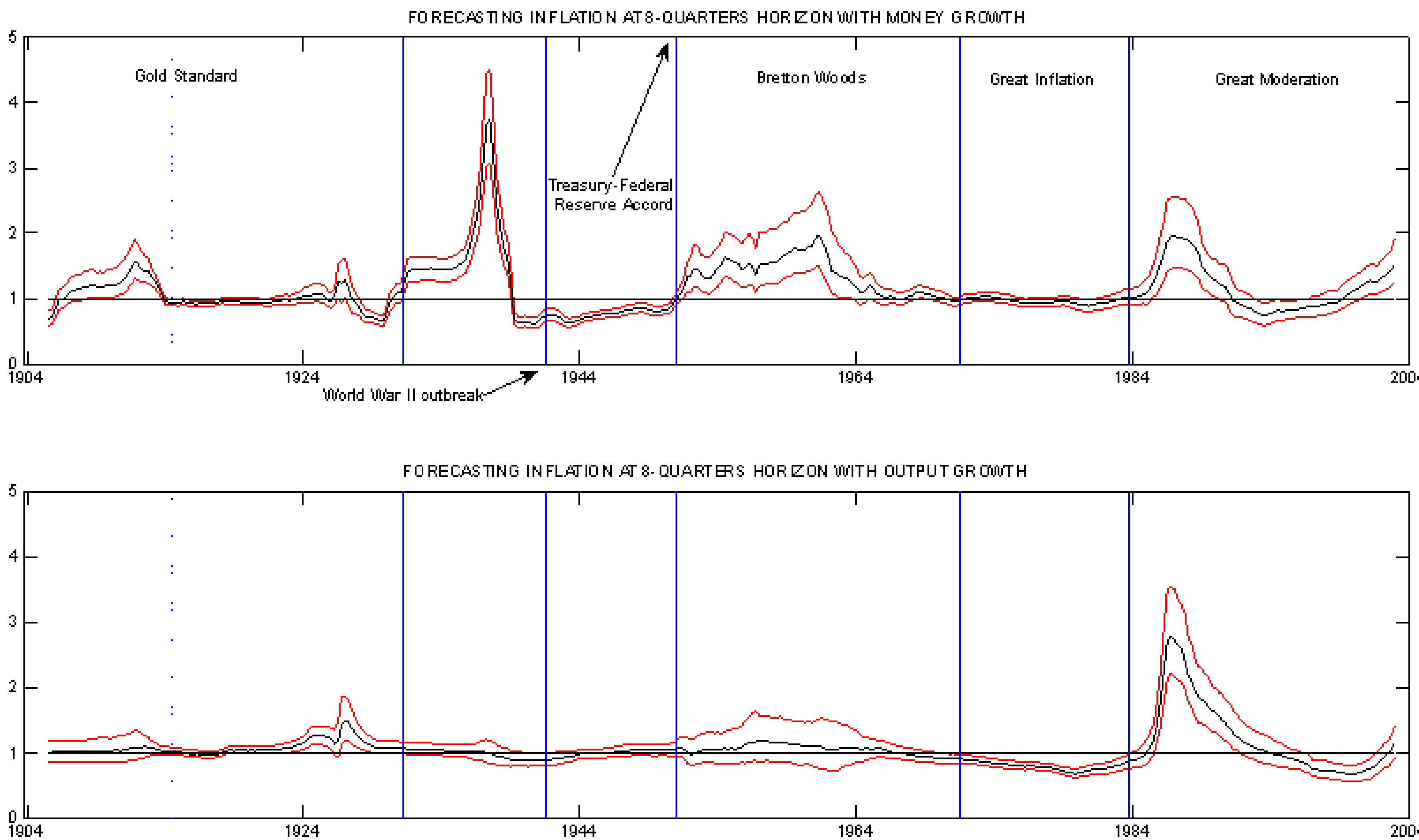

Figure 1: in the top (bottom) panel, relative SMSFEs at eight-quarters horizon (h=8) between a bivariate VAR in inflation and money growth (inflation and output growth), and a univariate model for inflation. Black lines are median estimates; red lines are 68% error bands. Vertical lines represent changes in the monetary regime. Predicted variable: inflation.

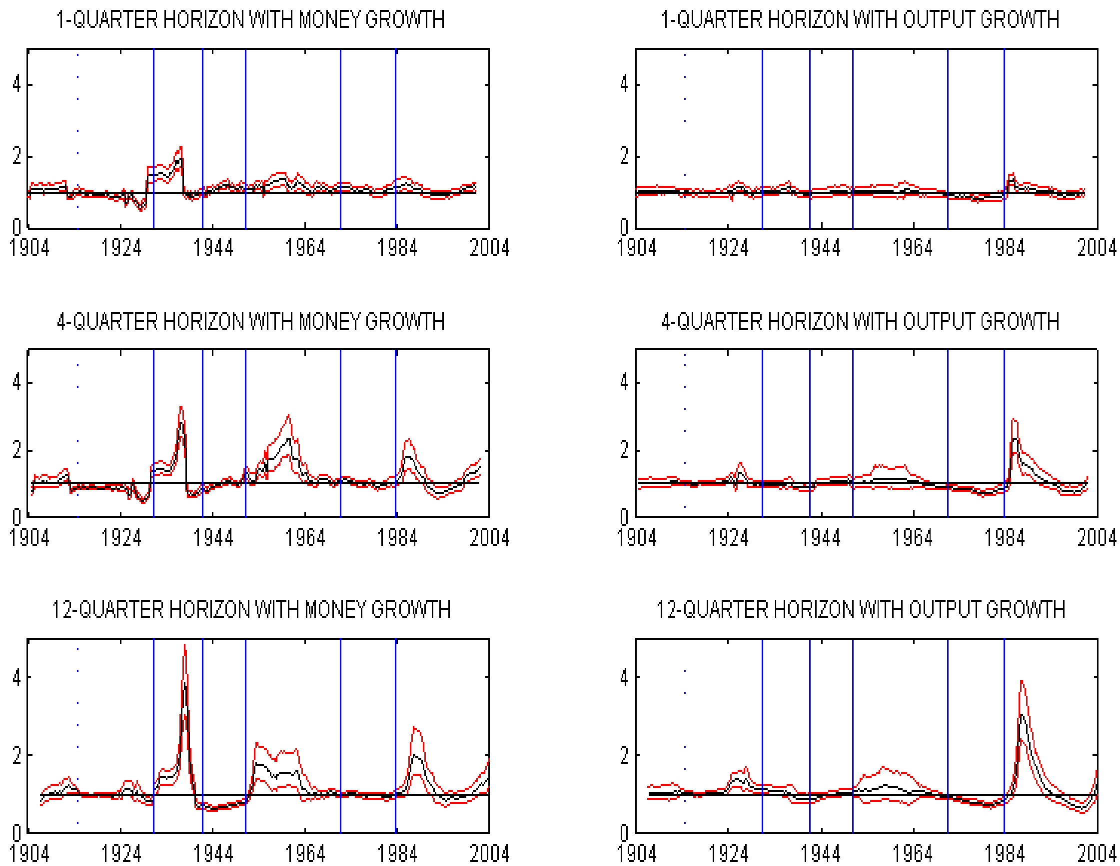

Figure 2: in the left (right) column, relative SMSFEs at one-, four- and twelve-quarters horizon (h=1, 4 and 12) between a bivariate VAR in inflation and money growth (inflation and output growth), and a univariate model for inflation. Black lines are median estimates; red lines are 68% error bands. Vertical lines represent changes in the monetary regime. Predicted variable: inflation.

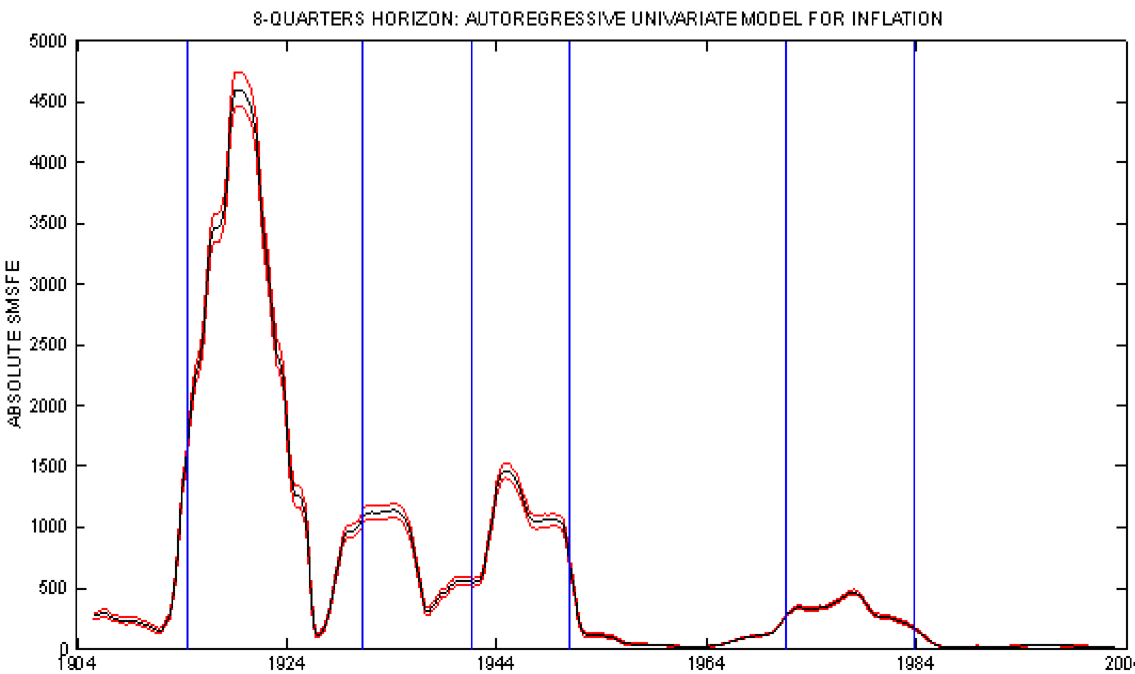

Figure 3: absolute SMSFEs at eight-quarters horizon (h=8) of the univariate benchmark model for inflation. Black lines are median estimates; red lines are 68% error bands. Vertical lines represent changes in the monetary regime.

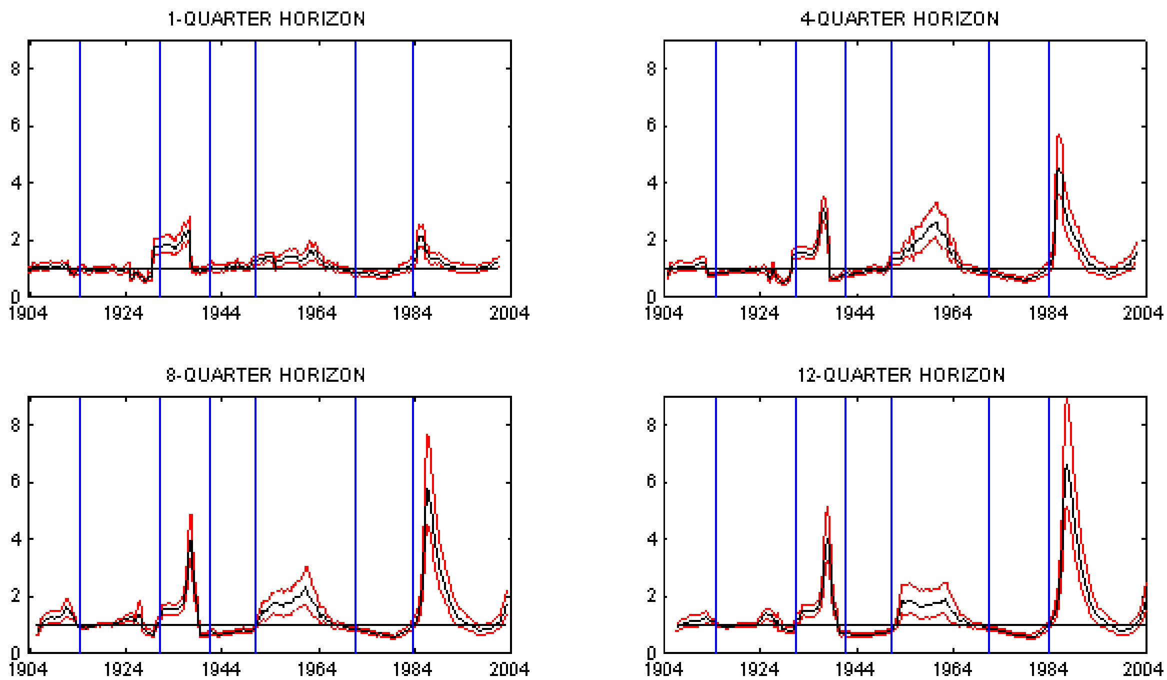

Figure 4: relative SMSFEs at one-, four-, eight- and twelve-quarters horizon (h=1, 4, 8 and 12) between a trivariate VAR in inflation, money growth and output growth, and a univariate model for inflation. Black lines are median estimates; red lines are 68% error bands. Vertical lines represent changes in the monetary regime. Predicted variable: inflation.

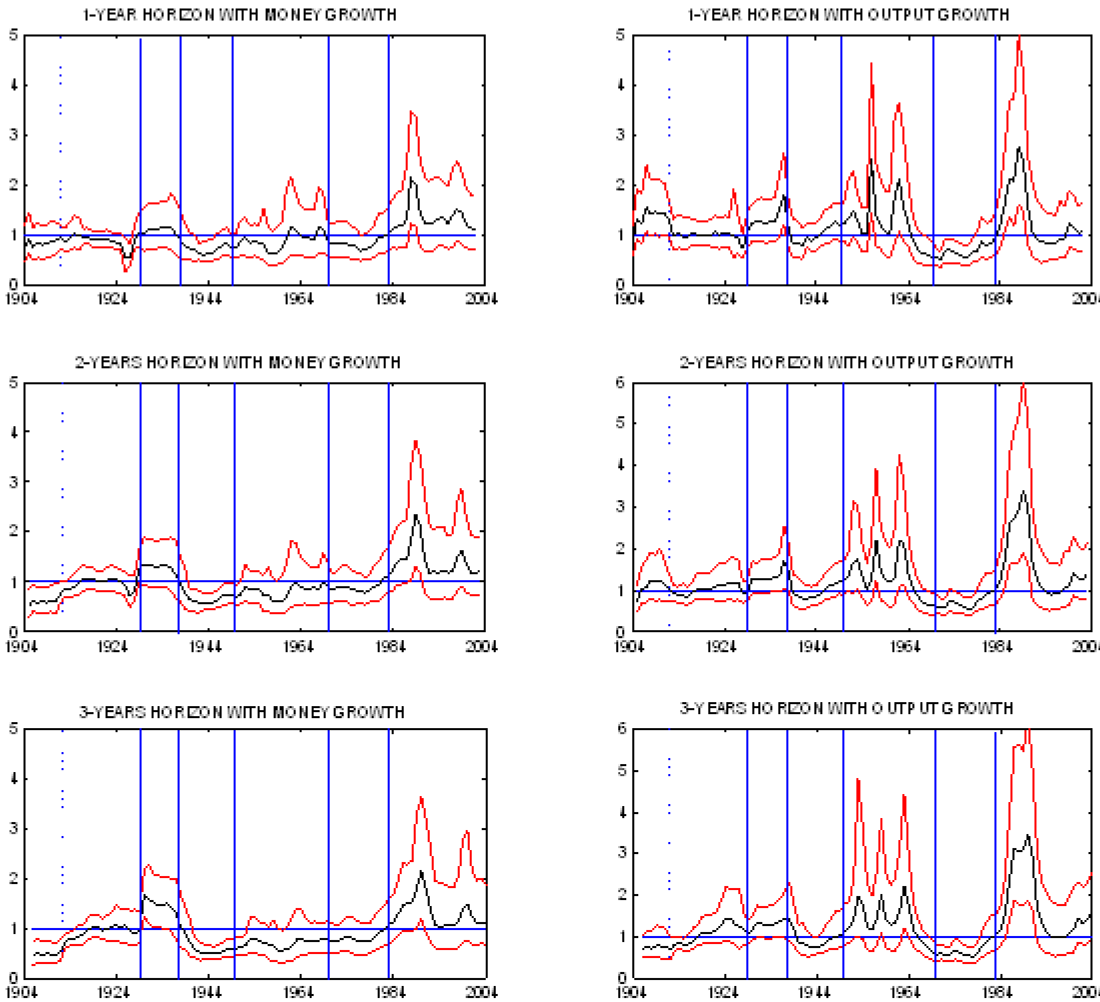

Figure 5: in the left (right) column, relative SMSFEs at one-, two- and three-years horizon between a bivariate VAR in inflation and money growth (inflation and output growth), and a univariate model for inflation fitted on annual observations. Black lines are median estimates; red lines are 68% error bands. Vertical lines represent changes in the monetary regime. Predicted variable: inflation.

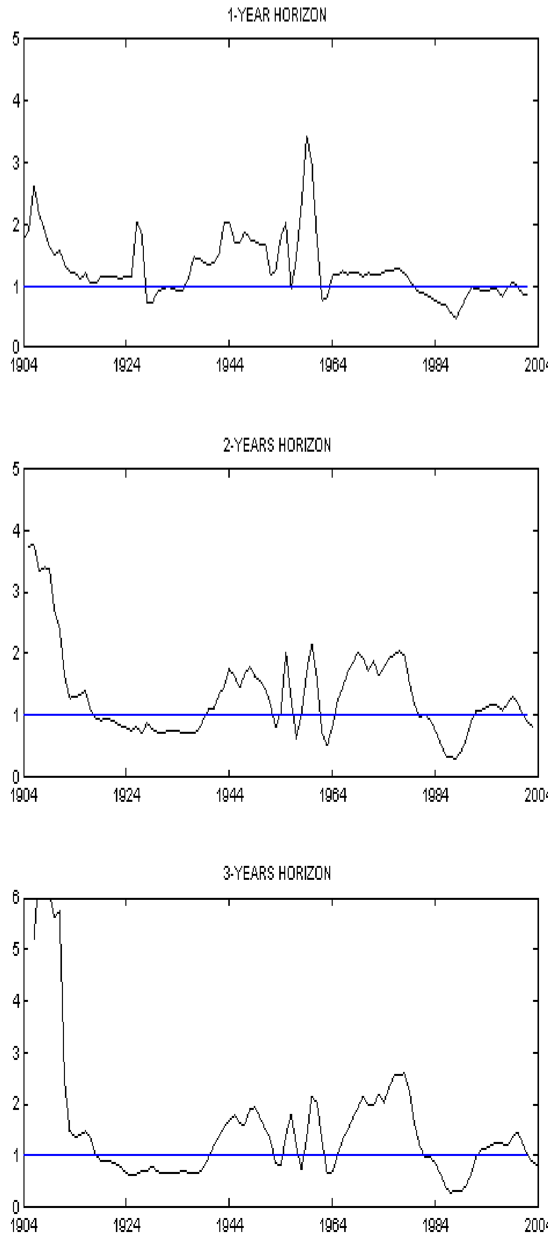

Figure 6: ratio of the SMSFEs at one-, two- and three-years horizon between a univariate model with drifting coefficients and stochastic volatility and a univariate model of unobserved components with stochastic volatility fitted on annual observations. Predicted variable: inflation.