Research Program on Forecasting

# Inflation Persistence: Revisited

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Abstract

This paper presents evidence on the persistence of inflation in the United States over the period 1947- 2010. Of particular interest is whether the persistence of inflation has changed over that time period. We use a reduced form approach to measuring inflation persistence, modeling inflation as an autoregressive process. We measure persistence as the half-life of a shock to that process. Our analysis employs both a frequentist approach and a Bayesian approach to identify breaks in inflation persistence. Both our frequentist and Bayesian results indicate that inflation persistence has undergone significant changes over the past 60 years.

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## 1. Introduction

This paper presents evidence on the persistence of inflation in the United States over the period 1947- 2010. Of particular interest is whether the persistence of inflation has changed over that time period. Models such as Fuhrer and Moore (1995) and Blanchard and Gali (2007) suggest that inflation persistence is a structural feature of the economy, and not likely influenced by the behavior of policy makers. Others such as Batini (2006), Beechey and Osterholm (2007), Benati (2008) and Mehra and Reilly (2009) present evidence that inflation persistence depends on the monetary regime in place; accommodative policy regimes generate higher persistence than non-accommodative policy regimes.

In this paper, we use a reduced form approach to measuring inflation persistence, modeling inflation as an autoregressive process. We measure persistence as the half-life of a shock to that process. Our approach differs from previous work. Our analysis begins with a frequentist approach to identify breaks in inflation persistence over the post-World War II period using the methodology introduced by Bai and Perron (1998). We then employ a Bayesian methodology to search for break dates. We search for both the location and the number of breaks. This allows us to calculate the changes in inflation persistence over the post-World War II period. We are not the first to use Bayesian techniques to investigate inflation persistence. Pivetta and Reis (2007) use a Bayesian technique, which allows for inflation persistence to slowly evolve over the sample. A potential drawback of their approach is that if there are breaks, rather than gradual shifts, in the persistence of inflation, their technique may not show a change in persistence because they estimate their models with a rolling data window. Our method allows us to identify several breaks in the persistence of inflation over the post-World War II period.

In contrast to the findings of Pivetta and Reis, both our frequentist and Bayesian results indicate that inflation persistence has undergone significant changes over the past 60 years. Both methods also support that changes in inflation persistence roughly correspond to changes in monetary policy regimes. Moreover, inflation persistence since the early 2000s is low with the half-life of a shock in the range of one-half to one quarter.

This paper is organized as follows. Section 2 presents a review of the relevant literature. Section 3 defines our measures of persistence. Section 4 presents the baseline frequentist results. Section 5 presents the results of our Bayesian estimation. Section 6 presents results from a higher order model and section 7 concludes.

## 2. Relevant Literature

Several recent studies on inflation persistence have come from researchers associated with the Inflation Persistence Network (IPN) [1]. We focus our literature review mainly on studies that use reduced form measures of inflation persistence or connect changes in persistence to changes in monetary policy regimes[2].

Dossche and Everaert, (2005) use a structural time series model to identify and measure various sources of Euro area and U.S. inflation persistence: changes in the central bank's inflation objective, imperfect or sticky information, persistence in the exogenous drivers of inflation, and intrinsic inflation. The part most relevant to our work is changes in the central bank's inflation objective. Dossche and Everaert find that inflation persistence is relatively low when the central bank is operating in a stable inflation environment and expected inflation is well anchored. They further suggest that during periods when a central bank is most likely to be interested in reducing the inflation rate, these two conditions are not likely to hold—inflation persistence will be high.

Hondroyiannis and Lazaretou (2004) investigate changes in inflation persistence in Greece from 1975 to 2003. During that time period, Greece experienced high variation in inflation and as well as changes in policy regimes. Despite the change in regimes and the large decline in inflation, Hondroyiannis and Lazaretou find only a small change in inflation persistence over that time period. They further point out, however that much of the persistence in the period after the regime change in 1997 was due to the persistent drop in inflation. Hondroyiannis and Lazaretou argue that low or declining inflation that is persistent is normatively different from rising or high inflation that is persistent. In other words, a persistently good state is desirable while a persistently bad state is not.

Levin and Piger (2002) measure U.S. inflation persistence over the period 1984-2003. They find inflation is highly persistent throughout the period. Accounting for a break in the intercept in the early 1990s, however, inflation persistence declines.

Pivetta and Reis (2007) (henceforth PR) examine several reduced form measures of inflation persistence using multiple techniques, including Bayesian estimation similar to ours.

[1] See Angeloni, et al. (2004) for a summary of several of the early papers produced by the IPN team.
[2] Fuhrer (2009) provides an overview of structural models of inflation persistence.

We detail the main differences between our approach and theirs in section 6. PR find that the persistence of inflation in the United States has been high and roughly unchanged since the mid-1960s.

Benati (2008) using time series data for several countries, finds that inflation persistence does vary with monetary regimes. Benati also examines the period prior to the collapse of the classical gold standard in 1914. He reports that inflation persistence was "virtually absent" during that early time period. Benati concludes that inflation persistence is not structural in the sense of Lucas (1976), or "intrinsic" as in Levin and Piger (2004).

Our paper adds to this literature in several ways. First, we consider a longer sample than either Levin and Piger (2004) or PR (2007). Second, we use both an AR(1) and AR(3) model of inflation for both the Consumer Price Index (CPI) and GDP deflator. Third, our Bayesian framework allows us to discover both the most probable number and location of breaks and from there estimate the half-life. These contributions enhance the current literature that exists on inflation persistence.

## 3. Inflation Persistence

Our measures of inflation are the annualized quarterly percent change of the CPI and the GDP deflator.[3] The CPI is converted to quarterly observations by simple average prior to calculating the inflation rate.

Our first measure of persistence is the half-life derived from the first order autoregressive coefficient on inflation in the AR(1) model:

$$\pi_t = \beta_0 + \beta_1 \pi_{t-1} + \varepsilon_t, \qquad (1)$$

where $\pi_t$ is the annualized quarterly inflation rate, $\varepsilon_t$ is the stochastic error, $\beta_0$ is the intercept and $\beta_1$ is the autoregressive parameter. The half-life (HL) of a shock to this equation is represented by:

$$HL = \frac{.5}{1-\beta_1} \qquad (2)$$

The advantage of the AR(1) is that the half-life is continuous variable. With higher order

[3] The full sample for both series is 1947:1-2011:1. The GDP deflator vintage is from the April 2011 GDP release.

AR or ARMA structures the half-life is derived from the impulse response function and is typically defined as the number of periods it takes for the marginal impact of the shock to fall below half of its initial impact.[4] A potential disadvantage of the AR(1) is that by ignoring higher order dynamics, we may be mismeasuring the degree of persistence. To assess the potential mismeasurement, we report (Section 6) the half-life of a shock using an AR(3) model for inflation.

The autoregressive approach to measuring reduced form inflation persistence has been used by many other researchers. Some of those researchers report the half-life, some report the largest autoregressive root, and others report the sum of the autoregressive coefficients. In general, these measures are ordinally equivalent. Of the various measures, the half-life is the most intuitive therefore we report it.

A different approach to our reduced-form method is to use structural models to explain inflation persistence. Fuhrer and Moore (1995), Gali and Gertler (1999) and Christiano, Eichenbaum and Evans (2005) present models that link current price setting to the past thus causing inflation to be persistent. Fuhrer (2009) summarizes the evidence on the structural causes of inflation persistence. Because our approach is reduced form, we are not able to distinguish among the various explanations for inflation persistence. Our focus is instead on whether the reduced form measure of persistence is stable. As pointed out by Batini (2006), the reduced form approach yields a mongrel estimate of persistence that includes the influences of monetary policy, the underlying pricing process, and the expectations formation mechanism. Thus, a finding that persistence has changed is consistent with any combination of changes in these three factors.[5] In section 7 we discuss possible connections between changes in the Federal Reserve's operating procedures, and our identified changes in inflation persistence.

## 4. Frequentist Results

Before applying our Bayesian technique we estimate a baseline set of results using the standard frequentist methodology of Bai and Perron (1998) to identify the most likely dates of parameter changes. For both measures of inflation we test for the location(s) of one through four

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[4] Focusing on the AR(1) model to capture time series dynamics is not without precedent. Patton and Timmerman (2012) and Stock and Watson (2002) argue that low-order autoregressive terms capture much of the dynamics in macroeconomic data.

[5] Two studies use changes in inflation dynamics to identify changes in monetary policy regimes. Kozicki and Tinsley (2005) use changes in inflation dynamics to back out changes in the Fed's monetary policy target. Beechey and Osterholm (2007) use changes in inflation dynamics to back out changes in the Fed's preferences for output stability.

breaks.[6]

Results from the frequentist breakpoint test on the AR(1) model of inflation are reported in Tables 1 and 2 for GDP deflator inflation and CPI inflation, respectively. Half-life is measured in quarters. For example, the half-life of a shock to the GDP deflator inflation rate pre-1965:2 (Table 1) is 1.131 quarters, which means it takes a little over one quarter for half of the effect of a shock to disappear.

The AIC and BIC model selection statistics reported suggest which of the models minimizes the penalized error sum of squares. But as is always the case with these statistics, it is not clear whether there are statistically significant differences among the various models. Therefore, another advantage of the Bayesian approach described in the following section is that we are able to use Bayes Factor to make finer distinctions among competing models. Thus, for our discussion of the frequentist results, we do not identify a "best" model with respect to the number of breaks.

Two patterns emerge across the models reported in Tables 1 and 2. First, inflation persistence appears to peak between the late 1960s and early 1990s. For the CPI inflation rate, the peak appears to coincide with the period of the Great Inflation.[7] For the GDP deflator inflation rate, the peak appears about a decade later in the 1980s. Second, the break dates are similar for the two inflation rates. Except for the one-break case, the differences in break dates across the two inflation rates range from one to four quarters. And even for the case of one break, the confidence intervals around the break dates identified overlap. Finally, we find that inflation persistence is quite low in the most recent sub-samples. For the GDP deflator inflation rate, the half-life is a little over one quarter (1.091 after 1990:3) and for the CPI inflation rate, the half life is roughly one-half quarter (.485 after 1990:3).

## 5. Bayesian Estimation

The frequentist results are suggestive of breaks in the degree of inflation persistence over the post-World War II period. But a limiting feature of the frequentist approach is that it treats breaks in the model parameters as discrete events whereas a Bayesian approach allows for a distribution of possible break dates. Thus, the Bayesian estimation calculates the probabilities of breaks in persistence, which allows for a greater possible variation in the outcomes in the half-

[6] We use a minimum window of 15% of the data for each sub-period, which reasonably constrains us to a maximum number of four breaks over the entire sample.

[7] Orphanides (2002) defines the period of the Great Inflation as the end of 1969 through the end of 1979.

life of inflation. The Bayesian approach also allows for a more direct identification of the "best" model using Bayes Factor.

Our approach is most closely aligned with PR (2007) but there are several important differences. The most obvious difference is that PR estimate persistence using an AR(3) model. We estimate persistence with both the AR(1) and the AR(3). The more important difference is in the priors imposed on the AR parameters. PR impose prior distributions on both the AR parameters and the random error terms as well as include a restriction that there is no unit root. We also impose similar priors on our AR parameters, but relax the condition that there could not be a unit root. Another key difference is that PR allow the AR parameters to gradually change through time, allowing the AR coefficients to update as new data points were observed whereas we calculate half-life before and after each potential break given by the estimation.

The nature of the estimation procedure for PR's parameters naturally leads to gradual changes in the estimates for the AR parameters. Alternatively, we assume that the AR parameters remain fixed for a given window of data. This is similar to Pesaran et al. (2005) who use a technique similar to ours to forecast T-bill rates. Instead of focusing on a gradual change in the model parameters, we determine breakpoints in time where the nature of the model changes. We assume that there are new regimes dictated by the breakpoints and estimate our AR parameters accordingly. This allows for more sudden changes in the behavior of the AR parameters than would generally be estimated if one were to use all previous data points when estimating the parameters.

When developing our model for inflation persistence, the relationship was modeled according to a time-series with a predetermined number of lags, parameterized by a vector of parameters $\theta$ corresponding to the time series and variance coefficients. However, we do allow the distribution of the coefficients to be unstable over time and subject to discrete breaks, $\tau = \{\tau_1, ..., \tau_K\}$. This gives rise to *K+1* sets of parameters, $\theta$, corresponding to the *K+1* regimes indicated by the breaks.

Utilizing a Bayesian framework and supposing that there are *K* discrete breaks in the model, we want to obtain information about the joint distribution of the location of the breaks, $\tau$, and the parameters, $\theta_j$, associated with each regime *j*. We use an informative prior that the breaks are centered on the dates identified by the frequentist method in section 4. We place a uniform prior on the location of each break $\tau_i$ over an interval $[a_i, b_i]$. The width of the uniform priors was required to be at least 20 quarters and breaks were restricted from occurring within 15 quarters of each other. No breaks were allowed to occur in the first or last ten percent of the data. Subject to these constraints, the results were robust to choice of the prior to the location of the break.

After specifying our prior beliefs about the nature of the location of the breaks, we address the parameters of the time series in the *K+1* regimes. Here, we assume that the parameters are drawn from common distributions, remaining the same across the entire regime and not changing with the addition of each new data point in the regime. We assume that the autoregressive coefficients $\beta_j$ with $j=1,2,...K+1$ are independent draws from a normal distribution $\beta_j \sim N(b_0, B_0)$ while the variances are independent identically distributed draws specified using a gamma distribution, specifically $\sigma_j^{-2} \sim Gamma(v_0, d_0)$. Using another level of hierarchy, we assume that $b_0 \sim N(\mu_\beta, V_\beta)$ and $B_0 \sim W(v_\beta, V_\beta^{-1})$ where *W* is the Wishart distribution and $\mu_\beta$, $V_\beta$, $v_\beta$, and $V_\beta$ are all hyperparameters that must be specified a priori. The parameters $v_0$ and $d_0$ are also assumed to be specified a priori.

Under the assumption of *K* breaks, the posterior distribution of interest is $p(\theta, \tau, b_0, B_0, v_0, d_0 \mid \pi)$ which includes the *K+1* regime coefficients and the prior locations and scales. To obtain information about this posterior, we use a Gibbs sampler with 10,000 iterations and a burn-in of 5,000 iterations to obtain draws from the full conditional distributions which converge to joint posterior. To do this, we first simulate the locations of the *K* breaks $\tau$ conditional upon the data and the parameters. Then, we simulate the parameters conditional upon the location of the breaks and the data.

The first step is to simulate the locations of the breaks, conditional on the knowledge that there are *K* breaks. The conditional distribution that break $\tau_i$ will occur at time point $t_0$ is equal to

$$p(\tau_i = t_0 \mid \theta, \pi) = \frac{p(\pi \mid \theta, \tau_i = t_0)p(\tau_i = t_0)}{\sum p(\pi \mid \theta, \tau_i = t_0)p(\tau_i = t_0)} \qquad (3)$$

where the sum is over all possible time points for the break to occur. Since the prior is assumed to be uniform over the interval $[a_i, b_i]$, this calculation simplifies to calculating the likelihoods of the data conditional upon the existing draws for the time series coefficients for each possible time location of the break. We obtain the cumulative sum of the ratios of these likelihoods over the sum of the likelihoods for the interval of possible break locations. By drawing a single observation from a *Uniform[0,1]* distribution, we can obtain the updated location of break $\tau_i$. Thus, while the frequentist results were considered when developing the prior for the location of the break, they are not imposed upon the Bayesian results due to the consideration of the posterior distribution of the break locations given the other parameters and the random sampling of the Gibbs sampler.

Now given the set of simulated breaks, the data is partitioned into *K+1* regimes. To obtain the conditional distributions of the regression components of the autoregressive model, note that conditional distributions of the $\beta_j$ are mutually independent with

$$\beta_j \mid \sigma_j^2, b_o, B_0, v_0, d_0, \tau, \pi \sim N(\gamma_j, V_{\beta_j}) \qquad (4)$$

with $V_{\beta_j} = (\sigma^{-2} X_j^T X_j + B_0)^{-1}$ and $\gamma_j = V_{\beta_j}(\sigma^{-2} X_j^T \pi_j + B_0^{-1} b_0)$ where $X_j$ is the matrix of observations of the predictor variables in the regime *j* and $\pi_j$ is the vector of observations of the dependent variable in regime *j*.

The densities of the location and scale parameters of the regression coefficients, $b_0$ and $B_0$ can be written as:

$$\begin{aligned} &b_0 \mid \beta, \sigma^2, B_{0,} v_0, d_0, \tau, \pi \sim N(\mu_{b_0}, \Sigma_{b_0}) \\ &B_0^{-1} \mid \beta, \sigma^2, b_{0,} v_0, d_0, \tau, \pi \sim W(v_{B_0}, V_{B_0}^{-1}) \end{aligned} \qquad (5)$$

where

$$\Sigma_{b_0} = (\Sigma_\beta^{-1} + (K+1) B_0^{-1})^{-1}$$

$$\mu_{b_0} = \Sigma_{b_0}\left( B_0^{-1} \sum_{j=1}^{J} \beta_j + \Sigma_\beta^{-1} \mu_\beta \right)$$

$$v_{B_0} = v_\beta + (K+1)$$

$$V_{B_0} = \sum_{j=1}^{J} (\beta_j - b_0)(\beta_j - b_0)^T + V_\beta$$

The posterior distribution of the variance term for each regime may be specified as:

$$\sigma_j^{-2} \mid \beta_j, b_0, B_0, v_0, d_0, \tau, \pi \sim Gamma\left( \frac{v_0 + \sum_{i=\tau_{j-1}+1}^{\tau_j} (\pi_i - X_i\beta_i)^T (\pi_i - X_i\beta_i)}{2}, \frac{d_0 + n_j}{2} \right) \tag{6}$$

where $n_j$ is the number of observations assigned to regime *j*. In our case, the location and scale parameters for the variance of the autoregressive parameters are specified a priori, but they can also be drawn using a Gibbs sampler and Metropolis-Hastings algorithm.

The Bayesian results are reported in Tables 3 and 4. We follow Jeffreys (1961) and Kass and Rafferty (1995) in using Bayes Factor to select the best-fitting model. Moving from the least complex (fewest number of breaks) to the most we select the model with the largest number of breaks for which the Bayes Factor, when comparing this model to the model with one less break, still exceeds 10 which corresponds to "strong" evidence for that number of breaks. For example, for GDP deflator inflation persistence comparing the three and two break models the Bayes Factor of 10.34 provides "strong" evidence in favor of three breaks. If we compare the four and three break models, the Bayes Factor of 5.75 is "substantial" evidence in favor of four breaks, but not "strong" evidence; therefore we select the three break model.[8] We follow these selection criteria for the remaining models.

Using the best model according to Bayes Factor[9], we compare the frequentist and Bayesian results. For the GDP deflator inflation rate, the breaks are similar except for the first break which occurs earlier in the 1960s. For the CPI inflation rate, both methods find a break in the early 1980s but the first break occurs earlier in the sample (early 1960s) and the third break occurs later in the sample (early 2000s).

Again using the best model while comparing the two inflation series under the Bayesian estimation we find that the first two breaks are similar—the early 1960s and the early 1980s. But the third break differs across the two series, occurring in the early 1990s for the GDP deflator

[8] Kass and Rafferty (1995) define the following ranges for Bayes Factor: 1-3.2, "not worth more than a bare mention;" 3.2-10, "substantial;" 10-100, "strong;" and >100 "decisive."
[9] The best model in the Bayesian AR(1) estimation is the three break model for both GDP deflator inflation and CPI inflation.

and in the early 2000s for the CPI. Half-life for both measures of inflation are low (1.1 to 1.5 quarters) in the early samples, peak during the 1960s and 1970s (6 to 12 quarters) and fall to less than one quarter in the most recent sub-samples (.64 to .98 quarters). The patterns are similar to those found with the frequentist method.

## 6. Results for AR(3)

As a robustness check, we present results for AR(3) models in Tables 5 through 8. The AR(1) model has the advantage of yielding a closed-form solution for half-life (equation (2)). Because the dynamics of the AR(3) are more complicated than the AR(1), we calculate the half-life of a shock by simulation. There is also a potential source of ambiguity in measuring the half-life in the presence of more complicated dynamics since the AR(3) models allow for oscillations in the impulse responses. We therefore present two measures of half-life. The first measure counts the number of quarters it takes for a shock to first drop below half its initial value. The second measure counts the number of quarters until the shock permanently falls below half its initial value. In the majority of cases, the two measures are identical and in those cases where they differ, all but one differs by only one quarter.

Tables 5 and 6 present the frequentist results for the AR(3) specifications. For the GDP deflator, the break dates mostly coincide with those from the AR(1) model. In the one break model the break occurs in the late 1950s; however, the confidence intervals overlap between the AR(1) and AR(3) specifications. In the three break model, the first break from each specification occurs at a similar time but the second and third breaks do not match. In particular, the second break from the AR(1) model aligns with the third break from the AR(3) model. The pattern of half-lives for the AR(3) model of the GDP deflator is slightly different from the pattern found with the AR(1) model. The results for all but the four-break model indicate a relatively high degree of persistence in the last sub-sample mostly due to the different alignment of the breaks. For the four-break model, the half-life is 1-quarter, which is similar to the four break model AR(1) result for the post-1990:3 sub-sample (1.091 quarters).

In Table 6 we report the persistence for the CPI inflation rate. The break dates and level of persistence are very similar to that found in the AR(1) model. Persistence peaks during the Great Inflation and declines to one quarter in the final sub-sample (1990:3-2011:1).

The Bayesian results for the AR(3) model are presented in Tables 7 and 8. Taking account of the higher order dynamics does not affect the number of the break dates identified by the Bayesian model. Using our Bayes Factor cut-off of 10, we find "decisive" or "strong" evidence of three breaks of both the CPI and GDP deflator inflation rates, respectively.

Even though the same number of breaks is preferred, the AR(3) model leads to a different set of break dates compared to the AR(1) model.[10] For both inflation rates in the Bayesian estimation of the three break AR(1) model we find the first break in the early 1960s but for the Bayesian estimation of the three break AR(3) model we find the first break in the early 1950s. The break date in the early 1950s corresponds to a period of high volatility in both inflation series during the Korean War. Because of its ability to capture higher order dynamics, the AR(3) model is more sensitive to changes in the volatility of inflation. For GDP deflator inflation, the second break in the AR(1) model corresponds to the third break in the AR(3) model. The break date in the early 1990s is not identified by the AR(3) model instead an additional break is identified in the later 1960s.

For CPI inflation the third break for both AR models align; however, there is a difference in when the second break occurs (early 1970s vs. early 1980s). Once again this may be picking up some changes in volatility that coincided with the Great Inflation. Nonetheless, the consistent result across the two inflation series is that inflation persistence is low (one quarter) in the most recent sub-samples (post 1980:3 for the GDP deflator and post 2001:1 for the CPI) and that inflation persistence fell from the previous sub-sample.

## 7. Summary and Conclusion

Based on both the frequentist and Bayesian methods, our results suggest that inflation persistence changed significantly over the post-World War II period. In the recent samples, inflation persistence since the early 2000's is low with the half-life of a shock falling in the range of one-half to one quarter.

Benati (2008), Mehra and Reilly (2009) and Conrad and Eife (2012) present evidence showing that persistence varies across monetary regimes. While we do not directly test that hypothesis, our results are roughly consistent with theirs. Figure 1 plots the Bayesian estimates of persistence for the AR(1) and AR(3) models with three breaks. We also list a few key dates—the Treasury-Fed Accord in early 1951, the closing of the gold window in late 1971, the Volker monetary policy experiment from late 1979 through early 1983 and the onset of the Great

[10] The AR(3) model for both the frequentist and Bayesian estimation put the first break earlier than the AR(1) models for the GDP deflator.

Moderation in early 1984. Inflation persistence increased during the Great Inflation of the 1970s and decreased around the time of the Volcker monetary experiment. We leave it to future research to explain why persistence dropped even further after 1990 for the GDP deflator and after 2000 for the CPI.

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Table 1: GDP Deflator Inflation Persistence
Endogenous Breakpoints Determined by Frequentist Method
AR(1) Model

| Zero Break | | One Break | | Two Breaks | | Three Breaks | | Four Breaks | |
|---|---|---|---|---|---|---|---|---|---|
| Sample | Half-Life | sub-samples | Half-Life (Confidence Interval) | sub-samples | Half-Life (Confidence Interval) | sub-samples | Half-Life (Confidence Interval) | sub-samples | Half-Life (Confidence Interval) |
| 1947:1-2011:1 | 1.296 (0.90,2.0) | 1947:2-1965:1 | 1.131 (0.65, 2.3) | 1947:2-1966:4 | 1.133 (0.67, 2.2) | 1947:2-1966:4 | 1.133 (0.67, 2.2) | 1947:2-1963:1 | 1.108 (0.61, 2.4) |
| | | 1965:2-2011:1 | 5.076 (3.2, 11.4) | 1967:1-1980:1 | 2.795 (1.5, 9.9) | 1967:1-1979:4 | 2.486 (1.3, 9.0) | 1963:1-1972:1 | 4.335 (1.8, $\infty$) |
| | | | | 1980:2-2011:1 | 1.963 (1.2, 4.1) | 1980:4-1990:3 | 6.76 (2.7, $\infty$) | 1972:2-1981:2 | 2.071 (0.97, 11.6) |
| | | | | | | 1990:4-2011:1 | 1.091 (0.65, 2.1) | 1981:3-1990:3 | 10.942 (3.4, $\infty$) |
| | | | | | | | | 1990:3-2011:1 | 1.091 (0.65, 2.1) |

Break Dates
(Confidence Intervals)

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| N/A | | 1965:2 (1963:2, 1978:4) | | 1967:1 (1966:1, 1973:2) | | 1967:1 (1966:1, 1973:3) | | 1963:1 (1959:3, 1987:1) | |
| | | | | 1980:2 (1980:2, 1984:1) | | 1980:4 (1978:2, 1984:2) | | 1972:2 (1969:4, 1974:2) | |
| | | | | | | 1990:4 (1983:3, 1993:2) | | 1981:3 (1980:3, 1982:4) | |
| | | | | | | | | 1990:4 (1985:2, 1994:2) | |
| | | | | | | | | | |
| AIC: | 969.82 | | 952.94 | | 942.92 | | 944.25 | | 946.75 |
| BIC: | 980.42 | | 974.14 | | 974.72 | | 986.65 | | 999.75 |

Note: The 95% confidence intervals, shown in parentheses, were calculated by bootstrap simulation.

Table 2: CPI Inflation Persistence
Endogenous Breakpoints Determined by Frequentist Method
AR(1) Model

| Zero Break | | One Break | | Two Breaks | | Three Breaks | | Four Breaks | |
|---|---|---|---|---|---|---|---|---|---|
| Sample | Half-Life | sub-samples | Half-Life (Confidence Interval) | sub-samples | Half-Life (Confidence Interval) | sub-samples | Half-Life (Confidence Interval) | sub-samples | Half-Life (Confidence Interval) |
| 1947:1-2011:1 | 1.376 (0.96, 2.1) | 1947:2-1981:1 | 3.78 (2.2, 10.2) | 1947:2-1966:3 | 1.346 (0.79, 2.77) | 1947:2-1966:3 | 1.346 (0.79, 2.77) | 1947:2-1962:3 | 1.337 (0.74, 3.09) |
| | | 1981:2-2011:1 | .976 (.64, 1.59) | 1966:4-1981:1 | 9.529 (3.5, ∞) | 1966:4-1981:1 | 9.529 (3.504, ∞) | 1963:4- 1971:4 | 4.430 (1.87, ∞) |
| | | | | 1981:2-2011:1 | 0.976 (0.64, 1.59) | 1981:2-1990:2 | 1.658 (0.79, 6.57) | 1972:1- 1981:1 | 7.655 (2.61, ∞) |
| | | | | | | 1990:3-2011:1 | 0.485 (0.21, 0.85) | 1981:2- 1990:2 | 1.658 (0.79, 6.57) |
| | | | | | | | | 1990:3- 2011:1 | 0.485 (0.21, 0.85) |

Break Dates
(Confidence Intervals)

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| N/A | | 1981:2 (1974:2, 1981:2) | | 1966:4 (1965:4, 1974:1) | | 1966:4 (1965:4, 1974:1) | | 1962:4 (1961:1, 1982:3) | |
| | | | | 1981:2 (1976:3, 1982:1) | | 1981:2 (1977:1, 1982:3) | | 1972:1 (1965:2, 1972:4) | |
| | | | | | | 1990:3 (1981:3, 1995:3) | | 1981:2 (1978:4, 1982:2) | |
| | | | | | | | | 1990:3 (1981:3, 1995:3) | |
| | | | | | | | | | |
| AIC: | 1151.88 | | 1131.25 | | 1111.05 | | 1109.05 | | 1112.41 |
| BIC: | 1162.48 | | 1152.45 | | 1142.85 | | 1151.46 | | 1165.41 |

Note: The 95% confidence intervals, shown in parentheses, were calculated by bootstrap simulation.

Table 3: GDP Deflator Inflation Persistence
Endogenous Breakpoints Determined by Bayesian Method
AR(1) Model

| One Break | | Two Breaks | | Three Breaks | | Four Breaks | |
|---|---|---|---|---|---|---|---|
| sub-samples | Half-Life | sub-samples | Half-Life | sub-samples | Half-Life | sub-samples | Half-Life |
| 1947:2-1951:2 | 4.063 (0.451,7.484) | 1947:2-1962:1 | 1.272 (0.642, 2.437) | 1947:2-1962:1 | 1.120 (0.672, 2.170) | 1947:2-1956:4 | 1.345 (0.611, 3.394) |
| 1951:3-2011:1 | 5.546 (3.235,10.012) | 1962:2-1982:2 | 5.545 (2.535, 14.874) | 1962:2-1980:4 | 5.918 (2.434, 14.098) | 1957:1-1969:3 | 4.432 (1.377, 15.974) |
| | | 1982:3-2011:1 | 1.484 (0.836, 2.757) | 1981:1-1990:4 | 1.865 (0.686, 3.963) | 1969:4-1980:4 | 4.139 (1.541. 13.359) |
| | | | | 1991:1-2011:1 | 0.984 (0.561, 1.621) | 1981:1-1990:2 | 1.772 (0.611, 4.336) |
| | | | | | | 1990:3-2011:1 | 1.023 (0.524, 1.943) |

Break Dates
(Credible Intervals)

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1951:3 (1951:3, 1952:3) | | 1962:2 (1961:4, 1964:2) | | 1962:2 (1961:4, 1964:4) | | 1957:1 (1956:4, 1958:2) | |
| | | 1982:3 (1980:3, 1985:3) | | 1981:1 (1980:2, 1982:4) | | 1969:4 (1969:2, 1971:2) | |
| | | | | 1991:1 (1986:2, 1994:1) | | 1981:1 (1980:2, 1982:3) | |
| | | | | | | 1990:3 (1984:3, 1994:2) | |
| Bayes Factors: | 1 break vs. 0 | | 2 breaks vs. 1 break | | 3 breaks vs. 2 breaks | | 4 breaks vs. 3 breaks |
| | >10,000 | | 3010 | | 10.34 | | 5.75 |

Note: The 95% confidence intervals, shown in parentheses, were calculated by bootstrap simulation.

Table 4: CPI Inflation Persistence
Endogenous Breakpoints Determined by Bayesian Method
AR(1) Model

| One Break | | Two Breaks | | Three Breaks | | Four Breaks | |
|---|---|---|---|---|---|---|---|
| sub-samples | Half-Life | sub-samples | Half-Life | sub-samples | Half-Life | sub-samples | Half-Life |
| 1947:2-1983:1 | 3.482 (2.018,7.074) | 1947:2-1960:1 | 1.598 (0.784, 3.696) | 1947:2-1960:1 | 1.534 (0.727, 3.182) | 1947:2-1957:3 | 1.552 (0.707, 3.431) |
| 1983:2-2011:1 | 0.652 (0.312,1.059) | 1960:2-1979:3 | 16.965 (3.636, ∞) | 1960:2-1980:1 | 11.982 (3.215, ∞) | 1957:4-1971:3 | 2.583 (1.113, 6.315) |
| | | 1979:4-2011:1 | 1.311 (0.439, 2.313) | 1980:2-2002:2 | 1.793 (0.688, 3.854) | 1971:4-1982:1 | 6.043 (1.746, 15.395) |
| | | | | 2002:3-2011:1 | 0.641 (0.207, 1.482) | 1982:2-2001:4 | 1.137 (0.624, 2.047) |
| | | | | | | 2002:1-2011:1 | 0.545 (0.166, 1.257) |

Break Dates
(Credible Intervals)

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1983:2 (1981:1, 1991:4) | | 1960:2 (1959:2, 1961:4) | | 1960:2 (1959:2, 1961:4) | | 1957:4 (1956:4, 1960:3) | |
| | | 1979:4 (1979:1, 1981:1) | | 1980:2 (1978:4, 1983:3) | | 1971:4 (1969:1, 1973:1) | |
| | | | | 2002:3 (2000:3, 2004:2) | | 1982:2 (1981:1, 1984:1) | |
| | | | | | | 2002:1 (2000:1, 2002:4) | |
| Bayes Factors: | 1 break vs. 0 | | 2 breaks vs. 1 break | | 3 breaks vs. 2 breaks | | 4 breaks vs. 3 breaks |
| | >10,000 | | >10,000 | | 54.39 | | 3.76 |

Note: The 95% confidence intervals, shown in parentheses, were calculated by bootstrap simulation.

Table 5: GDP Deflator Inflation Persistence
Endogenous Breakpoints Determined by Frequentist Method
AR(3) Model

| Zero Break | | | One Break | | | Two Breaks | | | Three Breaks | | | Four Breaks | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| sample | Half-Life | | sub-samples | Half-Life | | sub-samples | Half-Life | | sub-samples | Half-Life | | sub-samples | Half-Life | |
| | First crossing | Last crossing | | First crossing | Last crossing | | First crossing | Last crossing | | First crossing | Last crossing | | First crossing | Last crossing |
| 1947:1-2011:1 | 3 | 3 | 1947:2-1958:3 | 1 | 1 | 1947:2-1966:4 | 1 | 1 | 1947:2-1966:4 | 1 | 1 | 1947:2-1962:4 | 1 | 1 |
| | | | 1958:4-2011:1 | 5 | 5 | 1967:1-1980:3 | 3 | 3 | 1967:1-1972:1 | 2 | 5 | 1963:1-1972:1 | 2 | 5 |
| | | | | | | 1980:4-2011:1 | 7 | 7 | 1972:2-1981:2 | 3 | 3 | 1972:2-1981:2 | 3 | 3 |
| | | | | | | | | | 1981:3-2011:1 | 13 | 13 | 1981:3-1990:3 | 16 | 16 |
| | | | | | | | | | | | | 1990:4-2011:1 | 1 | 1 |

Break Dates
(Confidence Intervals)

| Zero Break | One Break | Two Breaks | Three Breaks | Four Breaks |
|---|---|---|---|---|
| N/A | 1958:4 (1957:1, 1974:2) | 1967:1 (1966:1, 1974:1) | 1963:1 (1961:1, 1971:2) | 1963:1 (1961:1, 1971:2) |
| | | 1980:4 (1978:3, 1983:2) | 1972:2 (1969:4, 1973:2) | 1972:2 (1969:4, 1973:2) |
| | | | 1981:3 (1980:4, 1983:1) | 1981:3 (1980:4, 1982:4) |
| | | | | 1990:4 (1982:2, 1996:1) |
| | | | | |
| AIC: 958.88 | 949.82 | 943.68 | 946.06 | 953.53 |
| BIC: 976.54 | 985.16 | 996.68 | 1016.72 | 1041.86 |

Column labeled first crossing denotes when the shock first dissipates below ½ and column labeled last crossing denotes when the shock remains below ½. Half-life is measured in quarters.

Table 6: CPI Inflation Persistence
Endogenous Breakpoints Determined by Frequentist Method
AR(3) Model

| Zero Break | | | One Break | | | Two Breaks | | | Three Breaks | | | Four Breaks | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| sample | Half-Life | | sub-samples | Half-Life | | sub-samples | Half-Life | | sub-samples | Half-Life | | sub-samples | Half-Life | |
| | First crossing | Last crossing | | First crossing | Last crossing | | First crossing | Last crossing | | First crossing | Last crossing | | First crossing | Last crossing |
| 1947:1-2011:1 | 2 | 2 | 1947:2-1981:1 | 5 | 5 | 1947:2-1966:3 | 2 | 2 | 1947:2-1966:3 | 2 | 2 | 1947:2-1959:3 | 2 | 2 |
| | | | 1982:2-2011:1 | 1 | 1 | 1966:4-1981:1 | 9 | 9 | 1966:4-1979:4 | 5 | 5 | 1959:4-1971:4 | 1 | 3 |
| | | | | | | 1981:2-2011:1 | 1 | 1 | 1980:1-1990:2 | 2 | 2 | 1972:1-1981:1 | 7 | 7 |
| | | | | | | | | | 1990:3-2011:1 | 1 | 1 | 1981:2-1990:2 | 2 | 2 |
| | | | | | | | | | | | | 1990:3-2011:1 | 1 | 1 |

Break Dates
(Confidence Intervals)

| | Zero Break | One Break | Two Breaks | Three Breaks | Four Breaks |
|---|---|---|---|---|---|
| | N/A | 1981:2 (1971:4, 1984:3) | 1966:4 (1965:4, 1975:2) | 1966:4 (1966:1, 1975:3) | 1959:4 (1958:3, 1968:2) |
| | | | 1981:2 (1975:2, 1982:1) | 1980:1 (1975:3, 1981:4) | 1972:1 (1967:1, 1972:4) |
| | | | | 1990:3 (1982:2, 1991:4) | 1981:2 (1979:1, 1982:2) |
| | | | | | 1990:3 (1981:4, 1993:2) |
| | | | | | |
| AIC: | 1137.75 | 1127.43 | 1114.09 | 1112.76 | 1120.16 |
| BIC: | 1155.42 | 1162.76 | 1167.09 | 1183.43 | 1208.50 |

Column labeled first crossing denotes when the shock first dissipates below ½ and column labeled last crossing denotes when the shock remains below ½. Half-life is measured in quarters.

Table 7: GDP Deflator Inflation Persistence
Endogenous Breakpoints Determined by Bayesian Method
AR(3) Model

| One Break | | | Two Breaks | | | Three Breaks | | | Four Breaks | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| sub-samples | Half-Life | | sub-samples | Half-Life | | sub-samples | Half-Life | | sub-samples | Half-Life | |
| | First crossing | Last crossing | | First crossing | Last crossing | | First crossing | Last crossing | | First crossing | Last crossing |
| 1947:2-1951:3 | 1 | 2 | 1947:2-1951:3 | 1 | 2 | 1947:2-1951:4 | 1 | 2 | 1947:2-1952:1 | 1 | 2 |
| 1951:4-2011:1 | 5 | 5 | 1951:4-1980:2 | 8 | 8 | 1952:1-1968:4 | 3 | 4 | 1952:2-1969:1 | 3 | 4 |
| | | | 1980:3-2011:1 | 1 | 1 | 1969:1-1980:2 | 4 | 5 | 1969:2-1980:2 | 4 | 5 |
| | | | | | | 1980:3-2011:1 | 1 | 1 | 1980:3-2002:1 | 1 | 1 |
| | | | | | | | | | 2002:2-2011:1 | 1 | 1 |

Break Dates
(Credible Intervals)

| One Break | Two Breaks | Three Breaks | Four Breaks |
|---|---|---|---|
| 1951:4 (1951:4, 1952:3) | 1951:4 (1951:4-1952:4) | 1952:1 (1951:4, 1952:4) | 1952:2 (1951:4, 1952:4) |
| | 1980:3 (1980:2-1999:4) | 1969:1 (1968:1, 1971:2) | 1969:2 (1968:1, 1971:2) |
| | | 1980:3 (1980:2, 1981:4) | 1980:3 (1980:3, 1983:3) |
| | | | 2002:2 (1990:1, 2003:1) |
| Bayes Factors: 1 break vs. 0 | 2 breaks vs. 1 break | 3 breaks vs. 2 breaks | 4 breaks vs. 3 breaks |
| >10,000 | 3198 | 45.25 | 3.54 |

Column labeled first crossing denotes when the shock first dissipates below ½ and column labeled last crossing denotes when the shock remains below ½. Half-life is measured in quarters.

Table 8: CPI Inflation Persistence
Endogenous Breakpoints Determined by Bayesian Method
AR(3) Model

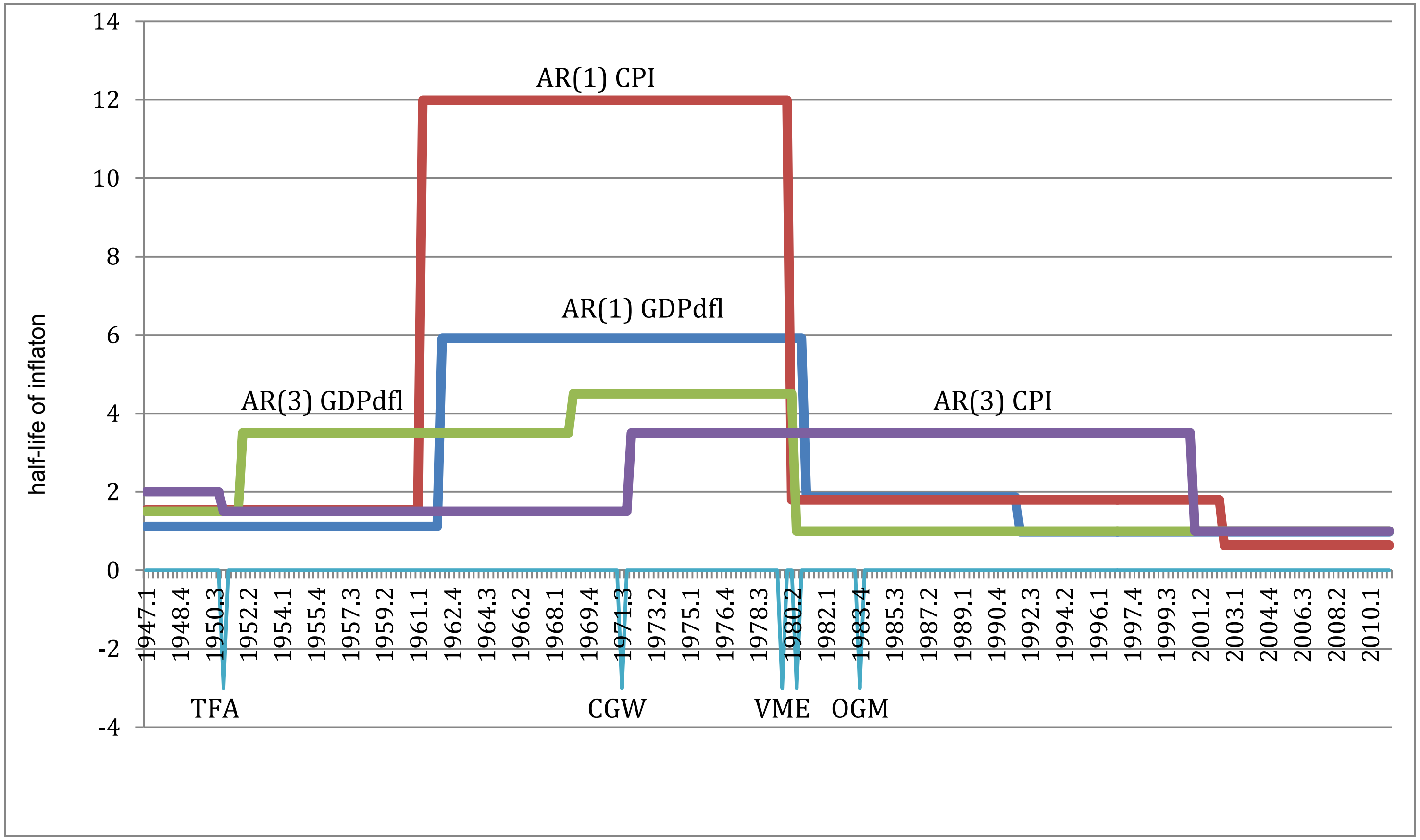
| One Break | | | Two Breaks | | | Three Breaks | | | Four Breaks | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| sub-samples | Half-Life | | sub-samples | Half-Life | | sub-samples | Half-Life | | sub-samples | Half-Life | |
| | First crossing | Last crossing | | First crossing | Last crossing | | First crossing | Last crossing | | First crossing | Last crossing |
| 1947:2-1959:4 | 2 | 2 | 1947:2-1951:3 | 2 | 2 | 1947:2-1951:4 | 2 | 2 | 1947:2-1951:3 | 2 | 2 |
| 1960:1-2011:1 | 2 | 2 | 1951:4-1980:4 | 2 | 6 | 1952:1-1971:4 | 1 | 3 | 1951:4-1971:4 | 1 | 2 |
| | | | 1981:1-2011:1 | 1 | 1 | 1972:1-2000:4 | 2 | 5 | 1972:1-1981:1 | 2 | 5 |
| | | | | | | 2001:1-2011:1 | 1 | 1 | 1981:2-2002:1 | 1 | 1 |
| | | | | | | | | | 2002:2-2011:1 | 1 | 1 |

Break Dates
(Credible Intervals)

| One Break | Two Breaks | Three Breaks | Four Breaks |
|---|---|---|---|
| 1960:1 (1959:2-1962:2) | 1951:4 (1951:4-1952:4) | 1952:1 (1951:4-1953:1) | 1951:4 (1951:4, 1952:4) |
| | 1981:1 (1979:3-2001:1) | 1972:1 (1968:3-1974:1) | 1972:1 (1970:3, 1973:3) |
| | | 2001:1 (1998:4-2001:4) | 1981:2 (1979:3, 1983:4) |
| | | | 2002:2 (2000:3, 2002:4) |
| Bayes Factors: 1 break vs. 0 | 2 breaks vs. 1 break | 3 breaks vs. 2 breaks | 4 breaks vs. 3 breaks |
| >10,000 | >10,000 | 288.46 | 3.67 |

Column labeled first crossing denotes when the shock first dissipates below ½ and column labeled last crossing denotes when the shock remains below ½. Half-life is measured in quarters.

Figure 1: Bayesian Estimates of Inflation Persistence




Notes:
TFA: Treasury-Fed Accord (1951:Q1)
CGW: Closing of the Gold Window (1971:Q3)
VME: Volcker Monetary Experiment (1979Q4-1983:Q1)
OGM: Onset of the Great Moderation (1984:Q1)