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Abstract: Using Bayesian tests for a structural break at an unknown break date, we search for a volatility reduction within the post-war sample for the growth rates of U.S. aggregate and disaggregate real GDP. We find that the growth rate of aggregate real GDP has been less volatile since the early 1980's, and that this volatility reduction is concentrated in the cyclical component of real GDP. The growth rates of many of the broad production sectors of real GDP display similar reductions in volatility, suggesting the aggregate volatility reduction does not have a narrow source. We also find a large volatility reduction in aggregate final sales mirroring that in aggregate real GDP. We contrast this evidence to an existing literature documenting an aggregate volatility reduction that is shared by only one narrow sub-component, the production of durable goods, and is not present in final sales. In addition to the volatility reduction in real GDP, we document structural breaks in the volatility and persistence of inflation and interest rates occurring over a similar time frame as the volatility reduction in real GDP.

Keywords: volatility reduction, stabilization, structural break, Bayesian

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1. Introduction

The U.S. economy appears to have stabilized considerably since the early 1980's as compared to the rest of the postwar era. For example, the standard deviation of quarterly growth rates of real U.S. GDP from 1950 through 1983 was over twice as large as for 1984 through 1999. This observation has sparked a growing literature rigorously testing the statistical significance of the volatility reduction and documenting various stylized facts about the nature of the stabilization. Recent additions to this literature include Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Kahn, McConnell and Perez-Quiros (2000), Ahmed, Levin and Wilson (2000) and Warnock and Warnock (2000).

Clearly, a primary goal of this literature is to determine the cause of the observed volatility reduction. Many explanations have been proposed, including improved policy (specifically monetary policy), structural change (a shift to services employment, better inventory management) and good luck (a reduction in real or external shocks). Determining the relative importance of these competing explanations is important in that they have very different implications for the sustainability of the volatility reduction and the evaluation of policy effectiveness. In assessing the viability of explanations for macroeconomic events, it is of course useful to have a clear picture of the nature of the event. In the current case, this includes compiling a list of stylized facts describing the volatility reduction. One can then ask whether these stylized facts invalidate any potential explanations for the reduction. In this paper we revisit an existing list of stylized facts that document how pervasive the volatility reduction is within broad production sectors of aggregate real GDP. [1] These stylized facts have been used in the existing literature

[1] Statistically, a volatility reduction in aggregate real GDP can arise from 3 sources: 1) Greater within-sector stability, 2) A shift in production shares to less volatile sectors (e.g. services) from more volatile sectors (e.g. manufacturing), 3) Changing covariances between sectors. In this paper we focus on documenting stylized facts regarding this first source.

as guidelines for identifying potential causes of the volatility reduction. In addition, we investigate structural change in the dynamics of nominal variables over this time period, namely inflation and interest rates.

This paper has four main findings: 1) Aggregate real GDP underwent a volatility reduction in the early 1980's that is shared by its cyclical component but not by its trend component. 2) A volatility reduction similar to that found in aggregate real GDP is present in many of the broad production sectors of real GDP. Thus, the volatility reduction in aggregate GDP is not confined to one sector. 3) Aggregate final sales underwent a volatility reduction similar to that seen in aggregate production. However, while durable goods production is one of the sectors displaying the largest volatility reduction in the early 1980's, final sales of durable goods do not become less volatile until the early 1990's. 4) The dynamics of inflation and interest rates have undergone structural breaks in persistence and conditional volatility that are consistent with existing monetary policy based explanations for the volatility reduction in real GDP.

Our results can be compared with those obtained by McConnell and Perez-Quiros (2000), hereafter MPQ, and Warnock and Warnock (2000). These papers conclude that a volatility reduction in broad measures of activity, (real GDP for MPQ, aggregate employment for Warnock and Warnock (2000)), is reflected in within-sector stabilization for only one sector - durable goods. MPQ go on to show that measures of final sales have not become more stable, suggesting the volatility reduction is focused in the behavior of inventories. The results of MPQ in particular can lead to striking conclusions regarding the viability of competing explanations for the source of the volatility reduction. For example, MPQ argue that explanations based on improved monetary policy are hard to reconcile with the limited breadth of the volatility reduction, particularly the failure of measures of final sales to show greater stability. They argue that explanations based on improved inventory management are much more consistent with the stylized facts. By contrast, the results presented here are consistent with a broad range of potential explanations. Indeed, we will argue that the evidence from broad production sectors of real GDP is not sharp enough to help invalidate potential candidates for the source of the volatility reduction.

The divergence between our results and the received literature are due in part to differences in the Bayesian framework of testing for a structural break used here, based on Chib (1995, 1998) and Kim and Nelson (1999), and classical tests such as those given in Andrews (1993) and Andrews and Ploberger (1994). Testing for structural change at an unknown date in the Bayesian framework has a distinct advantage over classical tests in the way information regarding the unknown break date is incorporated in the test. The unknown break date, which is a nuisance parameter present only under the alternative hypothesis, leads to non-standard asymptotic distributions for classical tests. As Koop and Potter (1999) point out, solutions to this problem in the classical framework fail to incorporate sample information regarding the unknown break point. Given that this sample information is potentially very relevant, classical tests can have low power. On the contrary, Bayesian model comparison incorporates sample information regarding the unknown break point and, as a byproduct of the test, yields the posterior distribution of the unknown break point.

In the following section we discuss the model specification and Bayesian methodology we use to investigate structural change in the conditional volatility of aggregate and disaggregate real GDP and the persistence and conditional volatility of inflation and interest rates. Section 3 presents the results of this investigation for aggregate and disaggregate real GDP while section 4 documents evidence regarding structural change in the persistence and conditional volatility of nominal variables such as the CPI inflation rate, the

Federal Funds rate and 10-year Treasury Bond rates. Section 5 concludes.

2 Model Specification, Bayesian Inference, and Model Comparison Techniques

2.1. Aggregate and Disaggregate Real GDP

To investigate a possible volatility reduction in growth rates of aggregate and disaggregate real GDP, we employ the following empirical model:

$$y_t = \sum_{j=1}^{k} \phi_j y_{t-j} + e_t, \tag{1}$$

$$e_t \sim N(0, \sigma^2_{D_t}) \tag{2}$$

$$\sigma^2_{D_t} = \sigma^2_0(1 - D_t) + \sigma^2_1 D_t \tag{3}$$

$$D_t = 0 \ for \ 1 \leq t \leq \tau \ \ and \ \ D_t = 1 \ for \ \tau < t \leq T - 1, \tag{4}$$

where y_t is the demeaned growth rate of the output series under consideration and D_t is a latent variable that determines the date of the structural break. In order to allow for the possibility of a permanent but endogenous structural break in the conditional volatility, we follow Chib (1998) and Kim and Nelson (1999) in treating D_t as a discrete latent variable with the following transition probabilities:

$$Pr[D_{t+1} = 0 | D_t = 0] = q, \quad Pr[D_{t+1} = 1 | D_t = 1] = 1, \tag{5}$$

$$0 < q < 1. \tag{6}$$

That is, before a structural break occurs, or conditional on $D_t = 0$, there always exists non-zero probability $1 - q$ that a structural break will occur, or $D_{t+1} = 1$. Thus, the expected duration of $D_t = 0$, or the expected duration of a regime before a structural break occurs, is given by $E(\tau) = \frac{1}{1-q_{00}}$. However, once a structural break occurs at $t = \tau$

(i.e., $D_\tau = 0$ and $D_{\tau+1} = 1$) we have $D_{\tau+j} = 1$ for all $j > 0$. We estimate two versions of the model given in 1-6, one in which a structural break is allowed, $(\sigma_0^2 \neq \sigma_1^2)$, and one in which there is no structural break, $(\sigma_0^2 = \sigma_1^2)$. Bayesian inference for the model allowing for structural change was performed using normal priors for $[\,\phi_1 \quad \ldots \quad \phi_k\,]'$, inverted Gamma distributions for σ_0^2 and σ_1^2, and a Beta distribution for q. In order to analyze the sensitivity of the empirical results to prior specifications for the parameters of the model, we employ the following three alternative sets of priors:

Prior #1: $[\,\phi_1 \quad \ldots \quad \phi_k\,]' \sim N(0_k, I_k)$; $\frac{1}{\sigma_0^2} \sim Gamma(1,2)$; $\frac{1}{\sigma_1^2} \sim Gamma(1,1)$; $q \sim Beta(8, 0.1)$

Prior #2: $[\,\phi_1 \quad \ldots \quad \phi_k\,]' \sim N(0_k, 2 * I_k)$; $\frac{1}{\sigma_0^2} \sim Gamma(1,4)$; $\frac{1}{\sigma_1^2} \sim Gamma(1,2)$; $q \sim Beta(8, 0.2)$

Prior #3: $[\,\phi_1 \quad \ldots \quad \phi_k\,]' \sim N(0_k, 0.5 * I_k)$; $\frac{1}{\sigma_0^2} \sim Gamma(1,1)$; $\frac{1}{\sigma_1^2} \sim Gamma(1,0.5)$; $q \sim Beta(8, 0.05)$

Priors employed for the linear model were based on those for $[\,\phi_1 \quad \ldots \quad \phi_k\,]'$ and σ_0^2 in Priors 1-3 above and yielded results very close to the maximum likelihood estimates. In the interest of brevity we will present only results for Prior #1 in the following sections. However, all results were quite robust to choice of prior.

To test for a structural break at an unknown break point based on the above benchmark model, we compare the model allowing for structural change to the model with no structural break using Bayes factors:

$$B_{10} = \frac{m(\tilde{Y}_T | \sigma_0^2 \neq \sigma_1^2)}{m(\tilde{Y}_T | \sigma_0^2 = \sigma_1^2)}, \tag{7}$$

where $\tilde{Y}_T = [\,y_1 \quad \ldots \quad y_T\,]'$ and $m(\tilde{Y}_T|.)$ is the marginal likelihood conditional on the model chosen. Among the various ways of evaluating the Bayes factor introduced in the literature, [2] we follow Chib's (1995) procedure in which the Bayes factor is evaluated through a direct calculation of the marginal likelihood based on the output from Gibbs sampling. Details of the Gibbs sampling procedure for the model allowing for structural change are described in the Appendix.

To aid in interpretation of the Bayes Factor, we will refer to the well-known scale of Jeffreys (1961) throughout the text:

$\ln(B_{10}) < 0,$	evidence supports the null hypothesis
$0 < \ln(B_{10}) \leq 1.15,$	very slight evidence against the null hypothesis
$1.15 < \ln(B_{10}) \leq 2.3,$	slight evidence against the null hypothesis
$2.3 < \ln(B_{10}) \leq 4.6,$	strong to very strong evidence against the null hypothesis
$\ln(B_{10}) > 4.6,$	decisive evidence against the null hypothesis

It should be emphasized that this scale is not a statistical calibration of the Bayes Factor but is instead a rough descriptive statement often cited in the Bayesian statistics literature.

2.2. Inflation and Interest Rates

The model in section 2.1 captures structural change in conditional volatility only, which preliminary investigation suggests is enough to adequately characterize structural change in real GDP. However, for inflation and interest rates, changes in persistence also appear to be important. Thus, to investigate structural change in the dynamics of inflation and interest rates we employ an expanded version of the model in section 2.1:

$$z_t = \mu_{D1_t} + \beta_{D1_t} z_{t-1} + \sum_{j=1}^{k} \phi_{j,D1_t} \Delta z_{t-j} + e_t, \tag{8}$$

$$e_t \sim N(0, \sigma^2_{D2_t}) \tag{9}$$

$$\mu_{D1_t} = \mu_0(1 - D1_t) + \mu_1 D1_t, \tag{10}$$

[2] Kass and Raftery (1995) provide a detailed survey of the literature.

$$\beta_{D1_t} = \beta_0(1 - D1_t) + \beta_1 D1_t, \tag{11}$$

$$\phi_{j,D1_t} = \phi_{j,0}(1 - D1_t) + \phi_{j,1} D1_t, \tag{12}$$

$$\sigma^2_{D2_t} = \sigma^2_0(1 - D2_t) + \sigma^2_1 D2_t, \tag{13}$$

where z_t is the level of the interest rate or inflation variable of interest and the latent variables $D1_t$ and $D2_t$ are independent $\{0, 1\}$ Markov-switching variables with transition probabilities:

$$Pr[Dk_{t+1} = 0 | Dk_t = 0] = q_k, \quad Pr[Dk_{t+1} = 1 | Dk_t = 1] = 1, \quad k = 1, 2 \tag{14}$$

$$0 < q_k < 1. \tag{15}$$

Here, β_{D1_t} captures a one-time shift in the persistence of the series z_t while σ_{D2_t} captures a shift in conditional volatility, which can occur at a different time from the shift in persistence. To prevent shifts in mean from generating spurious breaks in persistence we also allow for structural change in the constant term, μ_{D1_t}, that occurs at the same time as the break in persistence. Due to the added complexity of this model over that presented in section 2.1, we do not attempt to compare this model to one allowing for no structural change using Bayes Factors. Thus, we focus on what types of structural change the model captures by viewing the posterior means of the parameter estimates and the posterior distribution of the change point, but attempt no formal model comparison.

Estimation results reported are for the following prior specifications: $[\,\mu_j \quad \beta_j \quad \phi_{1j} \quad \ldots \quad \phi_{kj}\,]' \sim N((\,0 \quad 1 \quad 0 \ldots \quad 0\,)', 0.25 I_{k+2})$; $\frac{1}{\sigma^2_0} \sim Gamma(1, 2)$; $\frac{1}{\sigma^2_1} \sim Gamma(1, 1)$; $q_j \sim Beta(6, 0.1)$. Alternative priors were employed in which the variance of the parameters were halved and doubled. This did not change any of the results substantively.

3. Tests for a Volatility Reduction in Aggregate and Disaggregate Real GDP

In this section we evaluate the evidence of a stabilization in the growth rates of aggregate and disaggregate U.S. real GDP data. All data was obtained from DRI, covers the sample period 1960:I to 1998:II, is seasonally adjusted, and expressed in demeaned, quarterly growth rates. [3] The number of lags were chosen based on the AIC criterion for the model with no structural break. The AIC chose two lags for all series except consumption of non-durables and services, for which one lag was chosen. All inferences are based on 10,000 Gibbs simulations, after discarding the initial 2,000 simulations to mitigate the effects of initial conditions.

Table 1 summarizes the results of the Bayesian estimations and model comparisons for all the aggregate and disaggregate real GDP series considered. The second column of Table 1 presents the results of the Bayesian model comparison, summarized by the log of the Bayes factor in favor of a structural break. The third column of Table 1 shows the estimated break date derived from the expected duration of the state before the structural break occurs, $\frac{1}{1-\bar{q}}$, where $\bar{q}$ is the posterior mean of q. The fourth column of Table 1 presents $\frac{\bar{\sigma}_1^2}{\bar{\sigma}_0^2}$, the ratio of posterior means of the variance of e_t before and after the structural break. Finally, Figures 1-10 plot the estimated probability of a structural break at each point, $P(D_t = 1|\tilde{Y}_T)$, in time and the posterior distribution of the break date for each series under consideration.

3.1. Aggregate Real GDP, Trend, and Cycle

The first panel of Table 1 contains results for the growth rate of aggregate real GDP. The posterior mean of σ_1^2 is 21 percent of σ_0^2, consistent with a sizable reduction in volatility. The log of the Bayes factor is 14.87, decisive evidence against the model with

[3] In an effort to make our results comparable to the received literature we use data of a vintage prior to the October 1999 comprehensive NIPA revisions. Use of the revised data did not change our results substantively.

no volatility reduction, and the estimated break date is 1984.I, the same date reported in Kim and Nelson (1999) and MPQ. From Figure 1.B, the posterior distribution of the unknown break date is very tightly clustered around its posterior mode.

Next, we attempt to determine whether the trend and the cyclical component of real GDP have shared in this aggregate volatility reduction. It seems reasonable that at least a portion of the volatility reduction is due to a stabilization of cyclical volatility. Many plausible explanations for the volatility reduction, for example improved monetary policy and better inventory management, would mute cyclical fluctuations. However, some explanations, such as a lessening of oil price shocks, might also affect the variability of trend growth rates. Thus, investigating a stabilization in the trend and cyclical components might help shed light on the viability of competing explanations.

As is now well established in the literature, there are numerous ways of decomposing real GDP into a trend and cyclical component. Unfortunately, the choice of decomposition can have non-trivial implications for implied business cycle facts, see for example Canova (1998). In this paper we define the trend in the logarithm of real GDP, (LRGDP), as the logarithm of personal consumption of non-durables and services (LCNDS). Such a definition of trend is both theoretically and empirically plausible. Neo-classical growth theory, see for example the discussion in King, Plosser and Rebelo (1988), suggests that LRGDP and LCNDS share a common stochastic trend driven by exogenous, stochastic, technological change. This analysis suggests that LRGDP and LCNDS are cointegrated with cointegrating vector (1, -1). Recent investigations of the cointegration properties of these series confirm this result, see for example King, Plosser, Stock and Watson (1991) and Bai, Lumsdaine and Stock (1998). If one also assumes a simple version of the permanent income hypothesis, which suggests that LCNDS is a random walk, then LCNDS is the common stochastic trend shared by LRGDP and LCNDS. Although it is now well known that LCNDS is not a random walk, in the sense that one can find statistically significant predictors of future changes in LCNDS, Fama (1992) and Cochrane (1994) have argued that these deviations are so small as to be economically insignificant. Based on our measure of trend, we define the cyclical component of LRGDP as the residuals from a regression of LRGDP on a constant and LCNDS.

The second panel of Table 1 shows there is almost no evidence in favor of a break in the volatility of growth rates of LCNDS and therefore in our measure of the trend of log real GDP. The log of the Bayes factor is -0.4, providing slight evidence in favor of the model with no change in variance. However, the log of the Bayes factor for the level of the cyclical component, reported in the second panel of Table 1, is 12.1, providing decisive evidence against the model with no change in variance. The posterior mean of σ_1^2 is 24 percent of σ_0^2, close to the percentage for aggregate GDP. The estimated break date is 1983:IV and, from Figure 3.B, the posterior distribution of the break point is tightly clustered around this date. These results, which suggest that only the cyclical component of real GDP has undergone a large volatility reduction, makes explanations for the aggregate stabilization based on a reduction of real shocks to the trend component less compelling.

3.2 How Broad is the Volatility Reduction? Evidence for Disaggregate Data

In this section, we attempt to evaluate how pervasive the volatility reduction is across broad production sectors of the economy. To this end, we apply the Bayesian testing methodologies discussed above to broad production components of real GDP data. We use the same set of disaggregated data as MPQ to aid in comparisons with the prior literature.

Panel 3 of Table 1 contains the results for the first set of disaggregated data, a separation of real GDP into the production of goods, services and structures. The log of the Bayes Factor for goods production is 11.6, providing decisive evidence against the model with no change in volatility. The estimated break date is 1984:III, identical to the date estimated by MPQ using classical techniques. The log Bayes Factor for services production is 3.4, which, while still strong, is less so than for goods production. In addition, the estimated break date is 1966:II, not the early 1980's. Figure 5.B confirms this, showing no mass in the posterior distribution of the break date in the 1980's. Thus, it appears that services production is one sector that has not shared in the aggregate volatility reduction. The advantage of the Bayesian tests are most readily apparent for structures production. Classical tests used by MPQ find no evidence in favor of a volatility reduction in this sub-component of real GDP. However, the Bayesian tests find decisive evidence of such a reduction, the log Bayes factor is 8.4, with an estimated break date of 1984:IV. The volatility reduction in structures is quantitatively large as well, as the posterior mean of σ_1^2 is 33 percent of σ_0^2. Thus, in these broadly defined sectors of real GDP, both goods and structures production display strong evidence of a volatility reduction occurring around 1984.

Next, we decompose goods production into durable and non-durable goods production. From panel 4 of Table 1 there is decisive evidence against the model with no change in volatility for durable goods growth rates. The log Bayes factor is 13.4 and the estimated break date is the same as for aggregate GDP, 1984:I. The log Bayes factor for non-durables, 4.7, is smaller than for durables, but is still decisive evidence against the model with no break based on conventional metrics. The estimated break date is somewhat later than for durables, falling in the third quarter of 1986. Also, from Figure 7.B and 8.B, the posterior distributions of the break date for durables production is more tightly clustered around its posterior mode than that for non-durables production.

We have demonstrated that the volatility reduction in aggregate real GDP appears to be pervasive, extending to both goods and structures production in broad categories and to both durable and non-durable production within the goods category. Again, this is in contrast to MPQ who identify a volatility reduction only in the production of durable goods. Warnock and Warnock (2000) reach a similar conclusion as MPQ applying stochastic variance techniques to employment data. In addition, the tests performed by MPQ suggest that neither aggregate measures of final sales or final sales of durable goods have undergone a volatility reduction, a result that is strongly suggestive of a primary role for the behavior of inventories in explaining the aggregate volatility reduction. MPQ also argue that the failure of final sales to show any evidence of a volatility reduction casts doubt on explanations for the aggregate volatility reduction based on improved monetary policy. Here we too are interested in whether the broad based volatility reduction we identify in production data is also visible in final sales. To investigate this possibility we search for a volatility reduction in two final sales series: final sales of durable goods (FSD) and final sales of domestic product (FS), which is real GDP less inventory investment. [4]

From panel 5 of Table 1, the log of the Bayes Factor for FSD is 4.0, strong evidence against the model with no structural break. However, this evidence is weaker than when inventories are included, suggesting that inventory behavior is an important part of the early 1980's volatility reduction in durable goods production. This is further confirmed by the estimated break date for durable final sales, which is in the early 1990's. This break is much later than that recorded for aggregate GDP and durable goods production and is consistent with the findings of MPQ that final sales of durable goods did not undergo a volatility reduction in the early 1980's. However, aggregate final sales, measured by FS, does show evidence of a volatility reduction like that found in aggregate production. [5]

[4] As in MPQ, we also investigated final sales to domestic purchasers (FSDOM), which is FS less net exports. The results for FSDOM were nearly identical to those found for FS.

[5] In a paper written independent of this one, Ahmed, Levin and Wilson (2000) find that a test, described in Diebold and Chen (1996), that maximizes an F-statistic over candidate break dates also finds a statistically significant volatility reduction in aggregate final sales. As Ahmed, Levin and Wilson point out, this is somewhat puzzling given the similarity of their test to that used by MPQ.

The log of the Bayes Factor for FS is 5.2, decisive evidence against the model with no structural break. The posterior mean of σ_1^2 is 42 percent of the posterior mean of σ_0^2, a quantitatively large reduction. The estimated break date for FS is 1984:IV, similar to the estimate for aggregate real GDP. Notably, the posterior distribution of the break date for FS is bi-modal, having mass in both the early 1980's and early 1990's. The posterior distributions of the break point for FSD and FS, shown in Figures 9.B and 10.B, shows that both have mass in the early 1990's. However, while FSD has no mass in the early 1980's, FS has a majority of its probability mass over this time period.

In sum, our results suggest that evidence from broad production components of real GDP provide much less ammunition to invalidate any potential explanation for the aggregate volatility reduction than is suggested in the existing literature. Specifically, the volatility reduction appears pervasive across most of the production components and is present in measures of aggregate final sales in addition to production. Indeed, the evidence seems consistent with a broad range of explanations, including improved inventory management and improved monetary policy, and is thus not very helpful in narrowing the field of potential explanations.

One could still argue that our finding of a reduction in the volatility of durable goods production in the early 1980's, with no reduction in durable final sales volatility until the early 1990's, makes improved inventory management the leading candidate explanation for the volatility reduction within the durable goods sector. However, even this may not be a useful conclusion to derive from the stylized facts as there are reasonable explanations outside of improved inventory management that can explain the pattern of stabilization in final sales and production of durable goods. For example, suppose inventory corrections are non-linearly related to shortfalls in demand, only initiating when swings in demand cross some threshold. It is then possible that a small reduction in durable goods final sales volatility, perhaps small enough to be deemed statistically insignificant, might lead to a large reduction in the volatility of durable goods production. This could happen if the final sales volatility reduction was just enough to lower the number of times the threshold which triggers inventory corrections was crossed. In the case of the United States, the abnormally small number of manufacturing recessions since 1984 make this explanation a possibility.

4. Structural Change in the Dynamics of Inflation and Interest Rates

In this section we ask if the reduction in the volatility of real GDP identified in the previous section was accompanied by changes in the dynamics of nominal quantities such as inflation and interest rates. Specifically, we apply the model in equations (8)-(15), discussed in section 2.2, to growth rates of the consumer price index and levels of 10 year Treasury yields and the Federal Funds rate. Our investigation is similar to that in Watson (1999), who uses a Dickey-Fuller style equation as in (8) to document changes in the persistence and volatility of the Federal Funds rate and 10 year Treasury yields at a known break date. Our approach differs from Watson in that we allow for an endogenous break date. This, along with the Bayesian techniques employed, yields the posterior distribution of the break date, which is potentially quite interesting. Again, due to the added complexity of the model in (8)-(15) and in contrast to the results for real GDP, we focus only on estimation of the model allowing for structural change and do not attempt to compare these results to a model with no structural change using Bayes Factors. Thus, we focus on what types of structural change the model captures by viewing the posterior means of the parameter estimates and the posterior distribution of the change point, but attempt no formal model comparison.

Each series is expressed as quarterly averages and was standardized by dividing by its sample standard deviation. We investigate these series over the same time period as in Watson (1999), 1965:I to 1998:II. We should note that our analysis includes data from the late 1970's and early 1980's, a period of considerable volatility in inflation and interest rate series. To check the robustness of our results to the exclusion of this period, we also estimate linear versions of the model in (8)-(15) over the two subsample periods analyzed in Watson (1999), 1965:I-1978:3 and 1985:1-1998:2. For all series considered, the lag length was chosen based on the recursive procedure detailed in Campbell and Perron (1991) applied to the model with no structural break. The Bayesian estimation was based on 10,000 Gibbs simulations, after discarding the initial 2,000 simulations to mitigate the effects of initial conditions.

4.1 CPI Inflation

Table 2 summarizes the Bayesian inference of the parameters for the inflation rate. Several things are apparent from the posterior moments. First, the inflation rate has undergone a large drop in persistence. The posterior mean of the persistence parameter falls from $\beta_0 = 0.93$ before the structural break to $\beta_1 = 0.72$ after the break. Figure 11.B shows the posterior distributions of the two break dates. Note that the posterior distribution of the break point for the change in persistence is tightly clustered around its posterior mode, 1979:4. The parameter estimates indicate that the conditional variance also decreased dramatically, as the posterior mean of σ_1^2 is 20 percent of σ_0^2. The posterior distribution of the break date for the conditional volatility is tightly clustered around its posterior mode, 1990:1. This is substantially later than the reduction in persistence. However, given that the reduction in persistence implies a reduction in unconditional volatility, given by $\frac{\sigma^2_{D2_t}}{(1-\beta^2_{D1_t})}$, these results suggest two reductions in volatility, one at the beginning of the 1980's and another at the beginning of the 1990's. Finally, the constant term appears quite stable, suggesting the dominant features of any structural changes over the period analyzed is a reduction in the persistence and conditional volatility of inflation.

4.2 Ten-Year Treasury Yield

Table 3 presents the results for ten year Treasury bond yields. The posterior moments suggest a sizeable increase in conditional volatility, with the posterior mean of σ_1^2 being over 4 times as large as that for σ_0^2. The results also suggest a small decrease in the constant term, μ_{D1_t}, but no change in the persistence parameter, β_{D1_t}. The timing of the increase in volatility is very sharply defined, with the posterior distribution for $D2_t$, shown in Figure 12.B, very tightly clustered around its posterior mode, 1978:4. By contrast, given that no large structural change is identified in either the constant term or the persistence parameter for 10-year Treasury yields, we might expect the posterior distribution for $D1_t$ to be very diffuse. Indeed, Figure 12.B demonstrates this to be the case.

4.3 Federal Funds Rate

Table 4 holds the posterior moments for quarterly averages of the Federal Funds rate. The results are suggestive of a large decrease in the constant term and a slight increase in the persistence parameter, with the posterior mean of β_0 and β_1 equal to 0.91 and 0.95. However, the posterior distribution of the break date for the constant and persistence parameter, which is shown in Figure 13.B, is quite diffuse, suggesting that the data slowly gives information regarding a structural break in persistence over the course of the entire 1980's. This observation is consistent with Watson (1999), who suggests that, given the large sampling uncertainty associated with persistence measures near unity, the econometrician will learn about change in persistence only very slowly from observing realizations of the short rate. The model also picks up a substantial reduction in conditional volatility, with σ_1^2 less than 10 percent of σ_0^2 in both models. The break date is very precisely estimated, being tightly clustered around its posterior mode, 1985:I.

4.4 Results Excluding Data from 1979-1984

The results presented above for inflation and interest rates include data between 1979 and 1984, a period of considerable inflation and interest rate volatility. One might be concerned that our results are driven by the inclusion of data from this period. To investigate this, we estimate linear versions of the model in equation (8) for the period 1965:1-1978:3 and 1985:1-1998:2. [6] These are the same sub-periods considered by Watson (1999). As can be seen in Tables 5-7, our conclusions are robust to the exclusion of the volatile data. [7] The inflation rate continues to be characterized by a large reduction in persistence and conditional volatility, but by very little change in conditional mean. Likewise, the predominant change in the dynamics of ten year Treasury yields continues to be an increase in the conditional volatility of the series. Not surprisingly, this volatility increase is smaller with the exclusion of the very volatile data in the early 1980's. Finally, the Federal Funds rate is again characterized by a reduction in the constant term, an increase in persistence and a drop in conditional volatility. Here too, the difference in conditional volatility over the two sample periods is lessened by the exclusion of the volatile data.

4.5 Discussion

These results identify substantial changes in the time series dynamics of inflation and interest rates over the same time period that output growth became less volatile. While we will not attempt to argue that the pattern of structural change in these series gives definitive evidence regarding potential explanations for the volatility reduction in real

[6] To estimate these linear models we use priors based on a subset of the priors for the parameters for the model that allows for structural change. The estimates are very close to the maximum likelihood estimates.

[7] Whereas the results in Tables 2-4 are for standardized data, the results in Tables 5-7 are for unstandardized data, making comparison of the levels of the posterior moments between the two sets of tables difficult. However, the direction of change for the parameters undergoing structural breaks can be compared.

GDP, it is interesting to note that the evidence is very consistent with existing explanations based on improved monetary policy. Many authors, including Judd and Rudebusch (1998), Clarida, Gali and Gertler (1999), and Romer(1999) have argued that the monetary policy reaction function in the United States is characterized by two fundamental structural changes since the appointment of Chairman Volcker in 1979. First, the Federal Reserve seems to have become much more proactive in responding to deviations of inflation from target levels. In other words, the parameter on expected inflation in the Federal Reserve's reaction function has increased. Second, the Federal Reserve appears to have increased the amount by which they smooth changes in short-term interest rates. In other words, the Federal Reserve has placed increased weight on lagged values of the federal funds rate in its policy reaction function, thereby increasing the persistence of the federal funds rate ceteris paribus. As pointed out by Watson (1999), an increase in the persistence of short-term interest rates has implications for the volatility of longer term interest rates. The expectations theory of the term structure predicts that long term rates will be a weighted average of future short term rates. Thus, the amount of movement, or volatility, that will be seen in longer term rates for a given change in short rates increases with the persistence of changes in short rates. Simulations of neo-Keynesian model economies, such as those in Sack (1998), Levin, Wieland and Williams (1998) and Clarida, Gali and Gertler (1999), suggest that the sorts of changes to the Federal Reserve's reaction function described above may be optimal in the sense that they imply increased stability for the dynamics of inflation and output. In other words, these sorts of changes can move the economy to a more favorable inflation / output variability frontier.

When combined with the strikingly lower volatility of the cyclical component of GDP since the early 1980's, the results for inflation documented in this section suggest that we have indeed moved to a more favorable inflation / output variability frontier in the last two decades. The results also suggest that inflation has become much less persistent, consistent with a Federal Reserve that is more proactive in stamping out deviations of inflation from target levels. Also, the results for interest rates are very consistent with a Federal Reserve that has placed greater emphasis on persistence alongside its other policy goals since 1979. While we have not provided definitive evidence that the persistence of the Federal Funds rate has increased, the fact that there is any evidence of an increase in persistence is striking. This is because it occurs over a period when other variables of interest to the Federal Reserve, namely inflation and the cyclical component of output, have displayed lessened or stable persistence. As was discussed above, the persistence of inflation has decreased sharply since the early 1980's. The persistence of the cyclical component of output, which we have not discussed here, does not appear to have increased. This suggests that, all else being equal, the persistence of the Federal Funds rate should have fallen, not risen. That it has risen is suggestive of a deliberate effort by the Federal Reserve to increase the persistence of short term rates. We also find a substantial increase in the volatility of longer term interest rates, consistent with the expectation theory's prediction given the greater persistence in the Federal Funds rate.

5. Conclusion

In this paper, we use Bayesian tests for a structural break in variance to document some stylized facts regarding the volatility reduction in real GDP observed since the early 1980's. First, we find a reduction in the volatility of aggregate real GDP that is shared by its cyclical component but not by its trend component. Next, we investigate how pervasive this aggregate volatility reduction is across broad production sectors of real GDP. Evidence from the existing literature, which is based on classical testing procedures, has found that the aggregate volatility reduction has a narrow source, the durable goods sector, and that measures of final sales fail to show any volatility reduction. This evidence has been used to cast doubt on explanations for the volatility reduction based on improved monetary policy. By contrast, we find that the volatility reduction in aggregate output is visible in more sectors of output than simply durable goods production. Specifically, we find evidence of a volatility reduction in the production of structures and non-durables. We also find strong evidence of a reduction in the volatility of aggregate measures of final sales that looks similar to that in aggregate output. Based on these results, we argue that the evidence that one obtains from investigating the pattern of volatility reductions across broad production sectors of real GDP is not sharp enough to cast doubt on any potential explanations for the volatility reduction.

We also document changes in the dynamics of nominal variables such as inflation and interest rates over this same time period. We find evidence that, alongside the reduction in real GDP volatility, the persistence and conditional volatility of inflation has also fallen. Also, similar to Watson (1999), we find some evidence that the persistence of movements in the Federal Funds rate has increased over the last twenty years, accompanied by an increase in the volatility of ten year bond yields. We interpret these changes in terms of shifts in the weights placed on variables in the Federal Reserve's reaction function.

References

Ahmed, S., A. Levin and B.A. Wilson (2000), 'Recent U.S. Macroeconomic Stability: Good Policy, Good Practices, or Good Luck?', mimeo.

Andrews, D.W.K. (1993), 'Tests for parameter instability and structural change with unknown change point', *Econometrica,* 61, 821-856.

Andrews, D.W.K. and W. Ploberger (1994), 'Optimal tests when a nuisance parameter is present only under the alternative', *Journal of Econometrics,* 70, 9-38.

Bai, J., R.L. Lumsdaine and J.H. Stock (1998), 'Testing for and dating common breaks in multivariate time series', *Review of Economic Studies,* 65, 395-432.

Campbell, J.Y. and P. Perron (1991), 'Pitfalls and Opportunities: What Macroeconomists Should Know about Unit Roots,' *NBER Macroeconomics Annual,* 141-201.

Canova, F., 'Detrending and Business Cycle Facts', *Journal of Monetary Economics,* 41, 475-512.

Chib, S. (1995), 'Marginal likelihood from the Gibbs output', *Journal of the American Statistical Association,* 90, 1313-1321.

Chib, S. (1998), 'Estimation and comparison of multiple change-point models', *Journal of Econometrics,* 86, 221-241.

Clarida, R., Gali, J., and M. Gertler (1999), 'Monetary policy rules and macroeconomic stability: evidence and some theory', *Quarterly Journal of Economics*

Cochrane, J.H. (1994), 'Permanent and transitory components of GNP and stock prices', *Quarterly Journal of Economics,* 109, 241-263.

Diebold, F.X. and C. Chen (1996), 'Testing structural stability with endogenous breakpoint: A size comparison of analytic and bootstrap procedures', *Journal of Econometrics* 70, 221-241.

Fama, E.F. (1992) ‘Transitory variation in investment and output’, *Journal of Monetary Economics,* 30, 467-480.

Jeffreys, H. 1961. *Theory of Probability,* 3d ed. Oxford: Clarendon Press.

Judd, J.P. and G.D. Rudebusch (1998), ‘Taylor’s rule and the Fed: 1970-1997’, *Federal Reserve Bank of San Francisco Economic Review,* 3, 3-16.

Kahn, J., McConnell, M.M., and G.P. Quiros (2000), ’The Reduced Volatility of the U.S. Economy: Policy or Progress?’, mimeo.

Kass, R.E. and A. E. Raftery, ‘Bayes Factors’, *Journal of the American Statistical Association,* 90, 773-795.

Kim, C.-J. and C.R. Nelson (1999), ‘Has the U.S. economy become more stable? A Bayesian approach based on a Markov-switching model of the business cycle’, *The Review of Economics and Statistics,* 81, 608-616.

King, R.G., C.I. Plosser and S.T. Rebelo (1988), ‘Production, growth and business cycles II: new directions’, *Journal of Monetary Economics,* 21, 309-341.

King, R.G., C.I. Plosser, J.H. Stock and M.W. Watson (1991), ‘Stochastic trends and economic fluctuations’, *American Economic Review,* 81, 819-840.

Koop, G. and S.M. Potter (1999), ‘Bayes factors and nonlinearity: Evidence from economic time series’, *Journal of Econometrics,* 88, 251-281.

Levin, A., V. Wieland and J. C. Williams (1998), ‘Robustness of Simple Monetary Policy Rules under Model Uncertainty’, Federal Reserve Finance and Economics Discussion Paper. .

McConnell, M.M. and G.P. Quiros (2000), ‘Output fluctuations in the United States: What has changed since the early 1980’s?’, *American Economic Review,* 90, 1464-1476.

Romer, C.D. (1999), 'Changes in business cycles: evidence and explanations', *Journal of Economic Perspectives,* 13, 23-44.

Sack, B. (1998), 'Uncertainty, Learning, and Gradual Monetary Policy', Federal Reserve Finance and Economics Discussion Paper.

Warnock, M.V. and F.E. Warnock (2000), 'The Declining Volatility of U.S. Employment: Was Arthur Burns Right?', International Finance Discussion Papers, Federal Reserve Board.

Watson, M. W. (1999), 'Explaining the increased variability of long term interest rates', *Federal Reserve Bank of Richmond Economic Quarterly,* Fall 1999.

Woodford, M. (1999), 'Optimal monetary policy inertia', Working Paper, Princeton University.

Appendix: Calculation of the Marginal Likelihood Based on Gibbs Sampling for the Model in (1-6)

Define $\tilde{\theta} = [\,\tilde{\phi}' \quad \tilde{\sigma^2}' \quad q\,]'$ to be a vector of the parameters of the model, where $\tilde{\phi} = [\,\phi_1 \quad \ldots \quad \phi_k\,]'$ and $\tilde{\sigma}^2 = [\,\sigma_0^2 \quad \sigma_1^2\,]'$. Then, as in Chib (1995) the marginal density of $\tilde{Y}_T = [\,y_{k+1} \quad \ldots \quad y_T\,]'$, by virtue of being the normalizing constant of the posterior density, can be written as:

$$m(\tilde{Y}_T) = \frac{f(\tilde{Y}_T|\tilde{\theta})\pi(\tilde{\theta})}{\pi(\tilde{\theta}|\tilde{Y}_T)}, \qquad (A.1)$$

where the numerator is the product of the sampling density and the prior, with all integrating constants included, and the denominator is the posterior density of $\tilde{\theta}$. As the above identity holds for any $\tilde{\theta}$, we may evaluate $m(\tilde{Y}_T)$ at the posterior mean $\tilde{\theta}^*$. Taking the logarithm of the above equation for computational convenience, we have:

$$ln\ m(\tilde{Y}_T) = ln\ f(\tilde{Y}_T|\tilde{\theta}^*) + ln\ \pi(\tilde{\theta}^*) - ln\ \pi(\tilde{\theta}^*|\tilde{Y}_T) \qquad (A.2)$$

The log likelihood function and the log of the prior density at $\tilde{\theta} = \tilde{\theta}^*$ can be evaluated relatively easily. First, the log likelihood function is given by:

$$ln\ f(\tilde{Y}_T|\tilde{\theta}^*) = \sum_{t=k+1}^{T} ln(\sum_{D_t=0}^{1} p(D_t|\tilde{Y}_{t-1}, \tilde{\theta}^*) f(y_t|\tilde{Y}_{t-1}, D_t, \tilde{\theta}^*)), \qquad (A.3)$$

Second, the log of prior density is given by:

$$ln\ \pi(\tilde{\theta}^*) = ln\ \pi(\tilde{\phi}^*) + ln\ \pi(\tilde{\sigma^2}^*) + ln\ \pi(q^*), \qquad (A.4)$$

where it is a priori assumed that $\tilde{\phi}$, $\tilde{\sigma^2}$, and q are independent of one another.

Evaluation of the posterior density at $\tilde{\theta} = \tilde{\theta}^*$ is more demanding, but we can take advantage of the approach proposed by Chib (1995). For this purpose, consider the following decomposition of the posterior density:

$$\pi(\tilde{\theta}^*|\tilde{Y}_T) = \pi(\tilde{\phi}^*|\tilde{Y}_T)\pi(\tilde{\sigma^2}^*|\tilde{\phi}^*, \tilde{Y}_T)\pi(q|\tilde{\phi}^*, \tilde{\sigma^2}^*, \tilde{Y}_T), \qquad (A.5)$$

where

$$\pi(\tilde{\phi}^*|\tilde{Y}_T) = \int \pi(\tilde{\phi}^*|\tilde{\sigma^2}, \tilde{D}_T, q, \tilde{Y}_T)\pi(\tilde{\sigma^2}, \tilde{D}_T, q|\tilde{Y}_T)d\tilde{\sigma^2}d\tilde{D}_T dq \qquad (A.6)$$

$$\pi(\tilde{\sigma^2}^*|\tilde{\phi}^*, \tilde{Y}_T) = \int \pi(\tilde{\sigma^2}^*|\tilde{\phi}^*, \tilde{D}_T, q, \tilde{Y}_T)\pi(\tilde{D}_T, q|\tilde{\phi}^*, \tilde{Y}_T)d\tilde{D}_T dq, \qquad (A.7)$$

and

$$\pi(q^*|\tilde{\phi}^*, \tilde{\sigma^2}^*, \tilde{Y}_T) = \int \pi(q^*|\tilde{\phi}^*, \tilde{\sigma^2}^* \tilde{D}_T, \tilde{Y}_T)\pi(\tilde{D}_T|\tilde{\phi}^*, \tilde{\sigma^2}^* \tilde{Y}_T)d\tilde{D}_T \qquad (A.8)$$

The above decomposition of the posterior density suggests that $\pi(\tilde{\phi}^*|\tilde{Y}_T)$ can be calculated based on draws from the full Gibbs run, and $\pi(\tilde{\sigma^2}^*|\tilde{\phi}^*, \tilde{Y}_T)$, and $\pi(q^*|\tilde{\phi}^*, \tilde{\sigma^2}^*, \tilde{Y}_T)$ can be calculated based on draws from the reduced Gibbs runs. The following explains how each of these can be calculated based on output from appropriate Gibbs runs:

$$\hat{\pi}(\tilde{\phi}^*|\tilde{Y}_T) = \frac{1}{G}\sum_{g_1=1}^{G} \pi(\tilde{\phi}^*|\tilde{\sigma^2}^{g_1}, \tilde{D}_T^{g_1}, q^{g_1}, \tilde{Y}_T), \qquad (A.9)$$

$$\hat{\pi}(\tilde{\sigma^2}^*|\tilde{\phi}^*, \tilde{Y}_T) = \frac{1}{G}\sum_{g_2=1}^{G} \pi(\tilde{\sigma^2}^*|\tilde{\phi}^*, \tilde{D}_T^{g_2}, q^{g_2}, \tilde{Y}_T), \qquad (A.10)$$

$$\hat{\pi}(q^*|\tilde{\phi}^*, \tilde{\sigma^2}^*, \tilde{Y}_T) = \frac{1}{G}\sum_{g_3=1}^{G} \pi(q^*|\tilde{\phi}^*, \tilde{\sigma^2}^*, \tilde{D}_T^{g_3}, \tilde{Y}_T), \qquad (A.11)$$

where the superscript g refers to the $g-th$ draw of the full Gibbs run and the superscript g_i, $i = 1, 2, 3$, refers to the $g_i - th$ draw from the appropriate reduced Gibbs runs. Thus, apart from the usual G iterations for the full Gibbs run, we need additional $3\times G$ iterations for the appropriate reduced Gibbs run. In order to calculate $\pi(q^*|\tilde{\phi}^*, \tilde{\sigma^2}^*, \tilde{Y}_T)$, for example, we need output from an additional G iterations for the following reduced Gibbs run: i) Generate q from $p(q|\tilde{\phi}^*, \tilde{\sigma^2}^*, \tilde{D}_T, \tilde{Y}_T)$; ii) Generate $\tilde{D}_T$ from $p(\tilde{D}_T|\tilde{\phi}^*, \tilde{\sigma^2}^*, q\tilde{Y}_T)$. Notice that throughout the reduced Gibbs run, $\tilde{\phi}$ and $\tilde{\sigma^2}$ are not generated and they are set equal to $\tilde{\phi}^*$ and $\tilde{\sigma^2}^*$, respectively.

Table 1
Bayesian Tests for a Volatility Reduction in Aggregate and Disaggregate Real GDP

Variable	ln(BF)[1]	Break Point[2]	VR[3]
Real GDP	14.9	1984:I	0.21
Trend Component of GDP[4]	-0.4	–	–
Cyclical Component of GDP[5]	12.1	1983.IV	0.24
Goods	11.6	1984:III	0.27
Services	3.4	1966:II	0.38
Structures	8.4	1983:IV	0.33
Durables	13.4	1984:I	0.24
Nondurables	4.7	1986:III	0.42
Final Sales of Durable Goods	4.0	1992:I	0.20
Final Sales of Domestic Product	5.2	1984:IV	0.42

1. Log of Bayes Factor in favor of a structural break
2. Break point is estimated by the expected duration of a regime before structural break.
3. VR refers to ratio of variance after structural break to that before structural break
4. Trend component of log real GDP is approximated by log consumption of nondurables and services.
5. Cyclical component of log real GDP is defined as the residuals from a regression of log real GDP on a constant and log real consumption on nondurables and services.

Table 2
Posterior Moments for CPI Inflation

$$z_t = \mu_{D1_t} + \beta_{D1_t} z_{t-1} + \sum_{j=1}^{k} \phi_{j,D1_t} \Delta z_{t-j} + e_t,$$

$$e_t \sim N(0, \sigma^2_{D2_t})$$

$$Pr[Dk_{t+1} = 0 | Dk_t = 0] = q_k, \quad Pr[Dk_{t+1} = 1 | Dk_t = 1] = 1; \quad k = 1, 2$$

Parameters	Mean	Standard Error
μ_0	0.37	0.19
μ_1	0.37	0.16
β_0	0.93	0.05
β_1	0.72	0.08
ϕ_{10}	-0.05	0.15
ϕ_{11}	-0.32	0.11
ϕ_{20}	-0.23	0.15
ϕ_{21}	-0.38	0.10
σ^2_0	0.89	0.13
σ^2_1	0.17	0.06
q_1	0.984	0.015
q_2	0.990	0.009

Table 3
Posterior Moments for 10-Year Treasury Yields

$$z_t = \mu_{D1_t} + \beta_{D1_t} z_{t-1} + \sum_{j=1}^{k} \phi_{j,D1_t} \Delta z_{t-j} + e_t$$

$$e_t \sim N(0, \sigma^2_{D2_t})$$

$$Pr[Dk_{t+1} = 0 | Dk_t = 0] = q_k, \quad Pr[Dk_{t+1} = 1 | Dk_t = 1] = 1; \quad k = 1, 2$$

Parameters	Mean	Standard Error
μ_0	0.49	0.22
μ_1	0.31	0.39
β_0	0.97	0.02
β_1	0.95	0.04
ϕ_{10}	0.23	0.11
ϕ_{11}	0.16	0.33
ϕ_{20}	-0.11	0.11
ϕ_{21}	-0.07	0.30
σ^2_0	0.31	0.06
σ^2_1	1.41	0.24
q_1	0.988	0.013
q_2	0.982	0.018

Table 4
Posterior Moments for the Federal Funds Rate

$$z_t = \mu_{D1_t} + \beta_{D1_t} z_{t-1} + \sum_{j=1}^{k} \phi_{j,D1_t} \Delta z_{t-j} + e_t,$$

$$e_t \sim N(0, \sigma^2_{D2_t})$$

$$Pr[Dk_{t+1} = 0 | Dk_t = 0] = q_k, \quad Pr[Dk_{t+1} = 1 | Dk_t = 1] = 1; \quad k = 1, 2$$

Parameters	Mean	Standard Error
μ_0	0.58	0.24
μ_1	0.21	0.13
β_0	0.91	0.03
β_1	0.95	0.03
ϕ_{10}	0.28	0.14
ϕ_{11}	0.56	0.19
ϕ_{20}	-0.17	0.14
ϕ_{21}	-0.00	0.16
σ_0^2	1.48	0.25
σ_1^2	0.11	0.02
q_1	.987	0.013
q_2	.987	0.011

Table 5
Posterior Moments for Watson(1999) Sub-Samples: Inflation

	1965:1 - 1978:3		1985:1 - 1998:2	
Parameters	**Mean**	**Standard Error**	**Mean**	**Standard Error**
μ_0	1.05	0.52	1.09	0.57
β_0	0.80	0.07	0.65	0.05
ϕ_{10}	0.05	0.14	-0.17	0.12
ϕ_{20}	-0.19	0.14	-0.32	0.12
σ_0^2	2.35	0.48	1.85	0.38

Table 6
Posterior Moments for Watson(1999) Sub-Samples: 10-Year Treasury Yields

	1965:1 - 1978:3		1985:1 - 1998:2	
Parameters	**Mean**	**Standard Error**	**Mean**	**Standard Error**
μ_0	0.42	0.25	0.67	0.32
β_0	0.97	0.03	0.92	0.04
ϕ_{10}	0.22	0.14	0.38	0.14
ϕ_{20}	-0.17	0.14	-0.04	0.14
σ_0^2	0.10	0.02	0.19	0.04

Table 7
Posterior Moments for Watson(1999) Sub-Samples: Federal Funds Rate

	1965:1 - 1978:3		1985:1 - 1998:2	
Parameters	**Mean**	**Standard Error**	**Mean**	**Standard Error**
μ_0	0.94	0.42	0.24	0.17
β_0	0.87	0.06	0.95	0.03
ϕ_{10}	0.54	0.13	0.70	0.14
ϕ_{20}	-0.25	0.14	-0.10	0.14
σ_0^2	0.78	0.16	0.62	0.03

Figure 1.A. Probability of Structural Break:
Real GDP

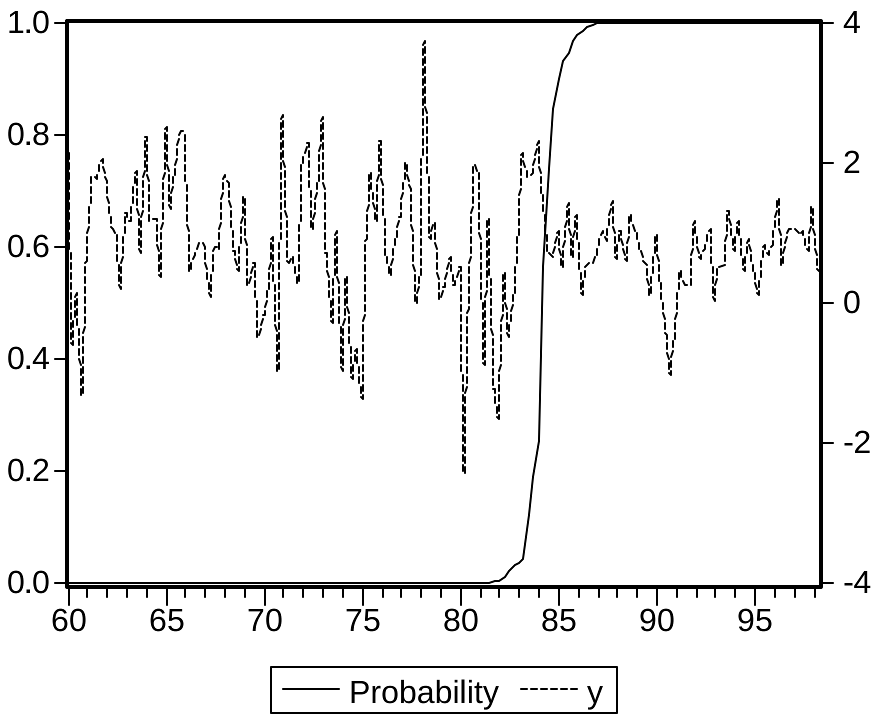

Figure 1.B. Posterior Distribution of Break Point:
Real GDP

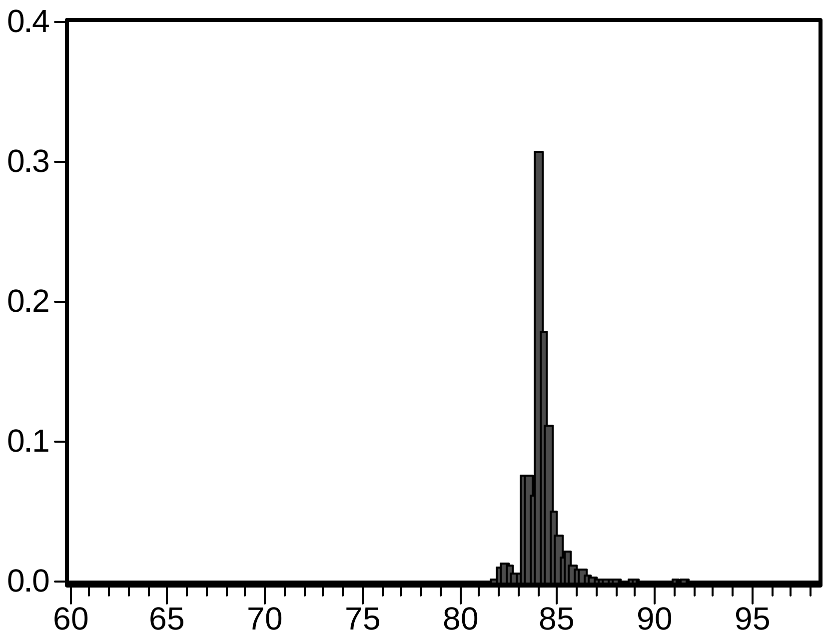

Figure 2.A. Cyclical Component of Real GDP and Probability of Structural Break

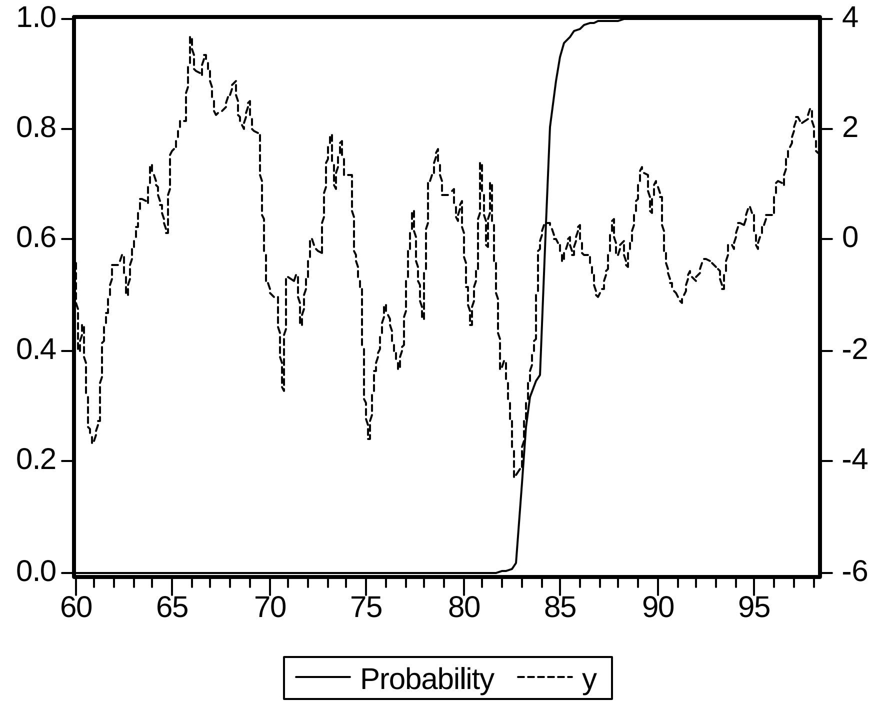

Figure 2.B. Posterior Distribution of Break Point: Cyclical Component of Real GDP

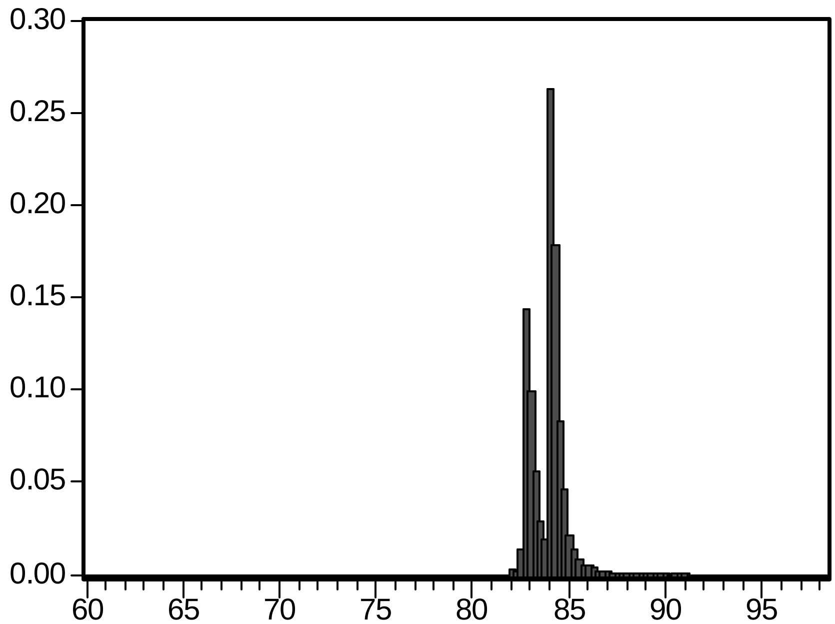

Figure 3.A. Trend Component of Real GDP and Probability of Structural Break

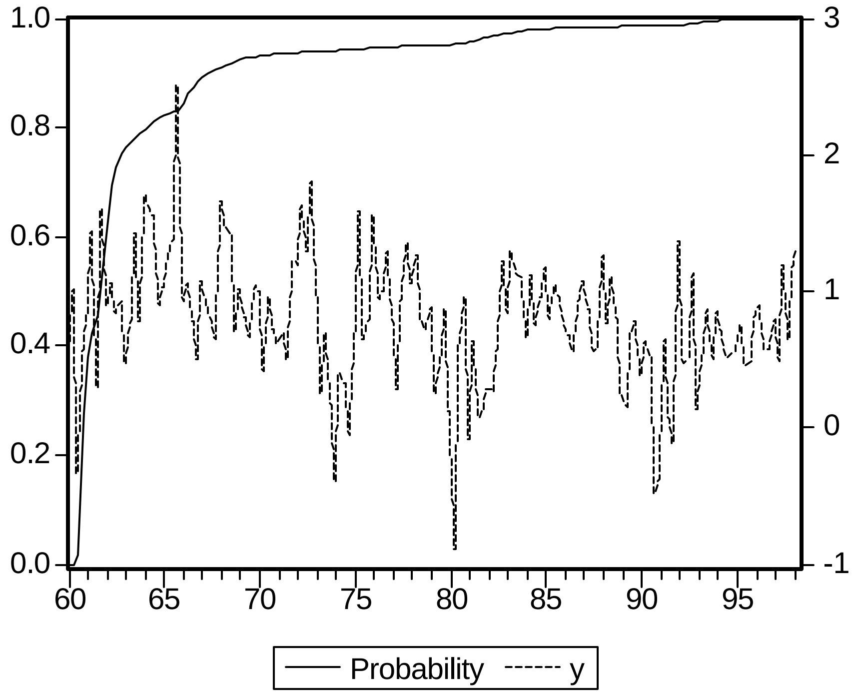

Figure 3.B. Posterior Distribution of Break Point: Trend Component of Real GDP

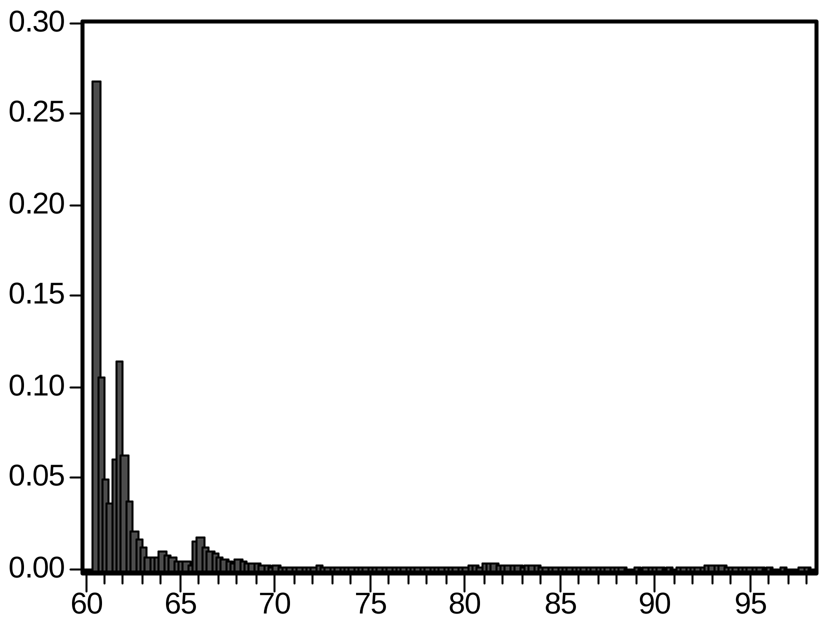

Figure 4.A. Goods Component of Real GDP and Probability of Structural Break

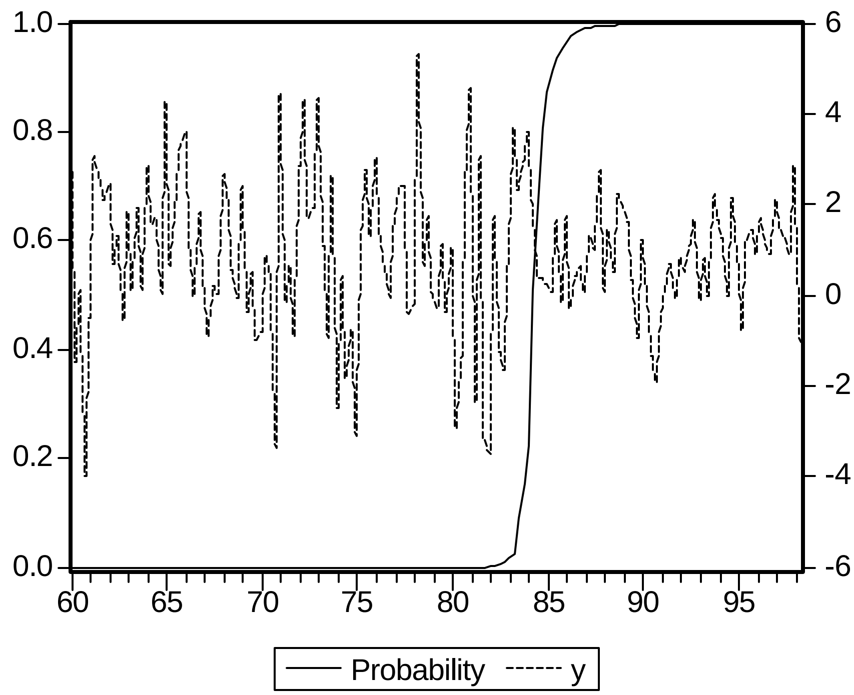

Figure 4.B. Posterior Distribution of Break Point: Goods Component of Real GDP

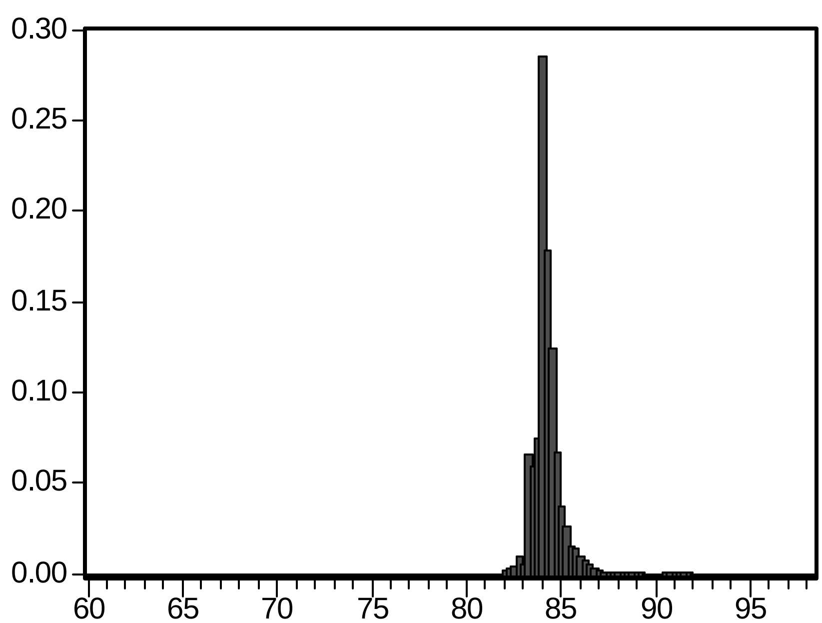

Figure 5.A. Services Component of Real GDP and Probability of Structural Break

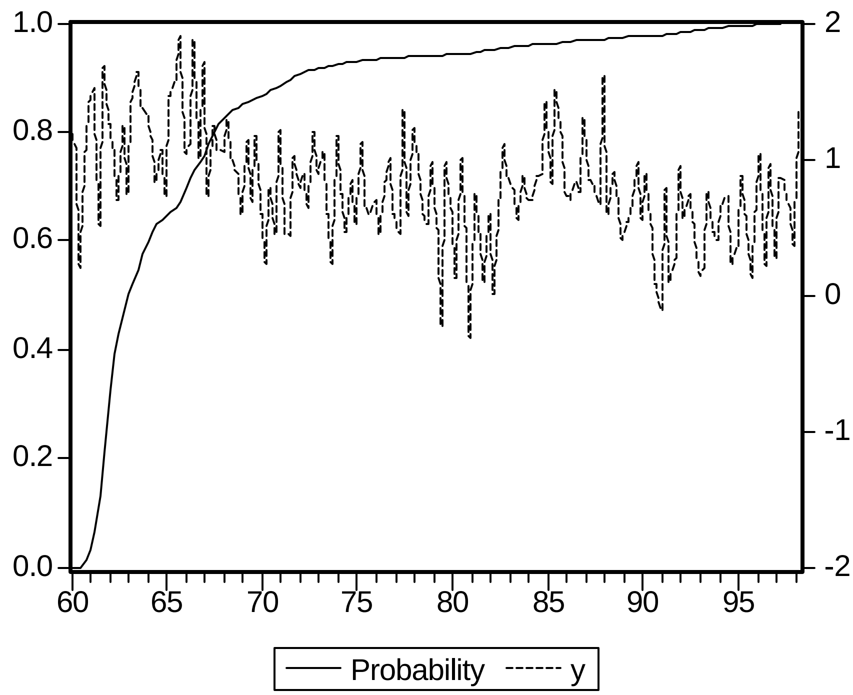

Figure 5.B. Posterior Distribution of Break Point: Services Component of Real GDP

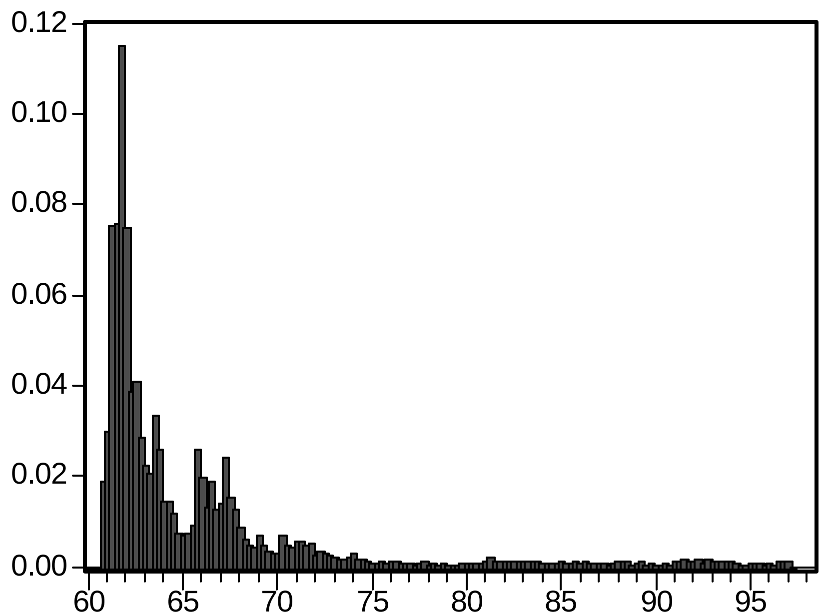

Figure 6.A. Structures Component of Real GDP and Probability of Structural Break

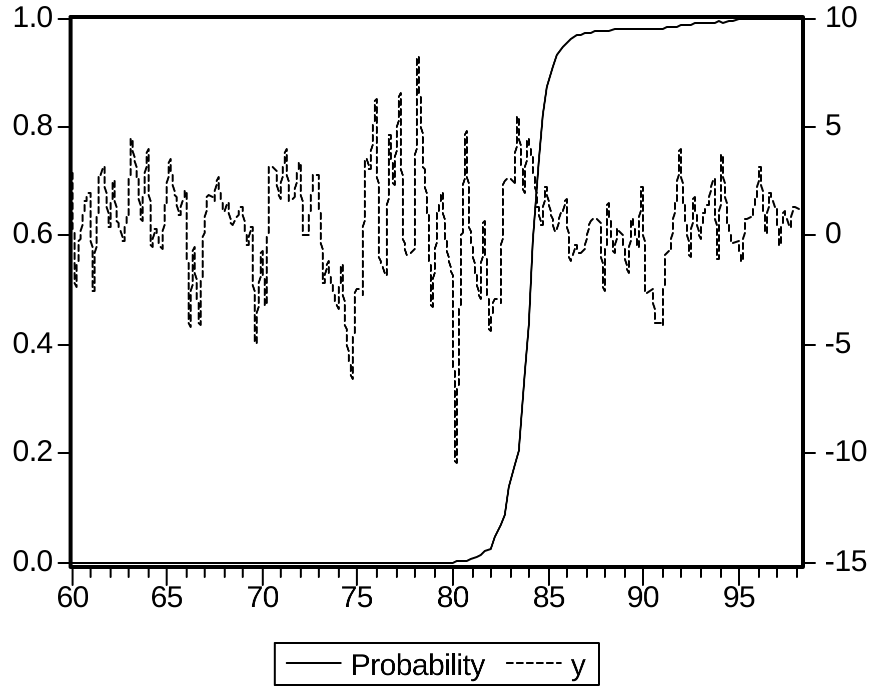

Figure 6.B. Posterior Distribution of Break Point: Structures Component of Real GDP

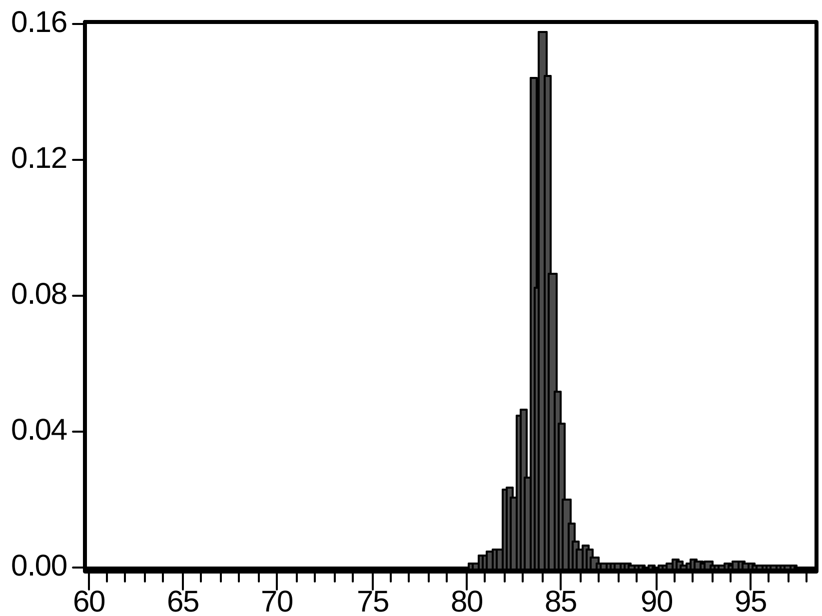

Figure 7.A. Durables and Probability of Structural Break

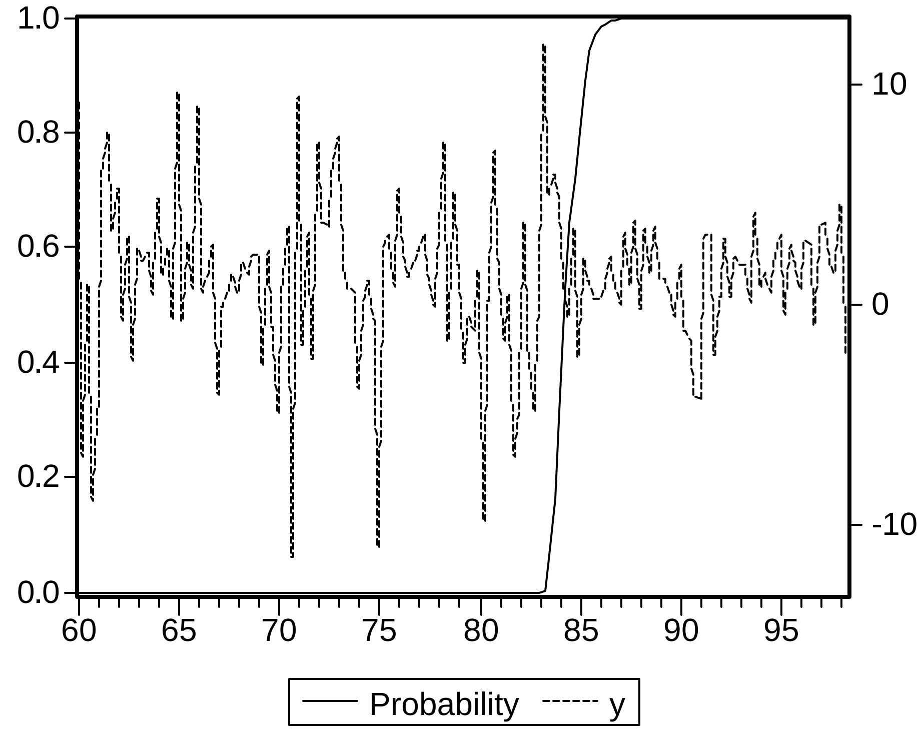

Figure 7.B. Posterior Distribution of Break Point: Durables

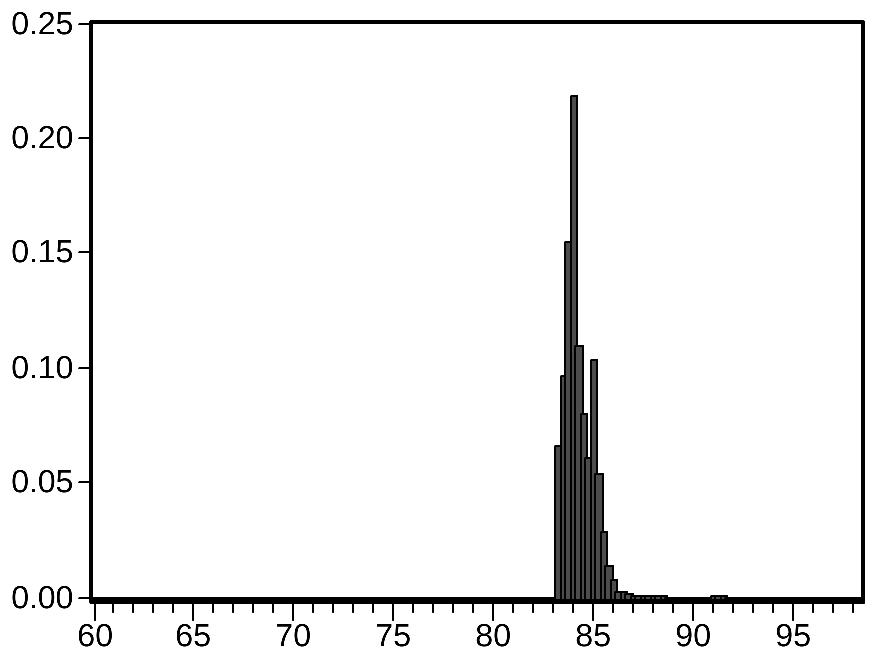

Figure 8.A. Nondurables and Probability of Structural Break

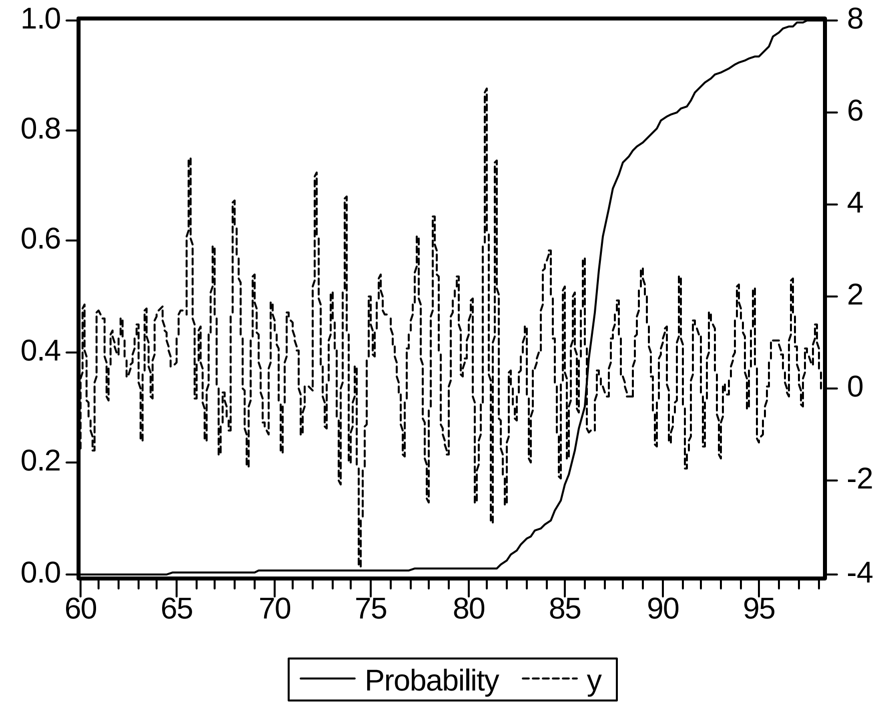

Figure 8.B. Posterior Distribution of Break Point: Nondurables

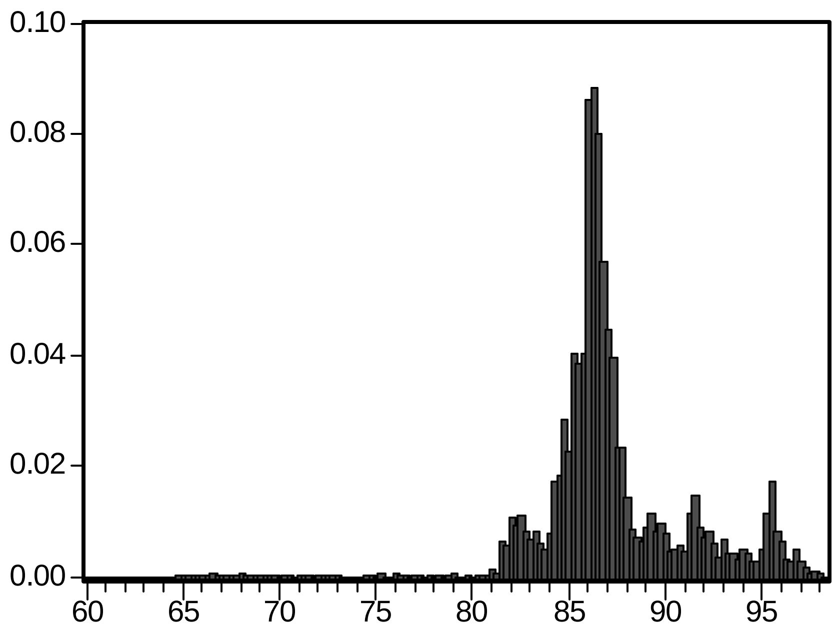

Figure 9.A. Durables Final Sales and Probability of Structural Break

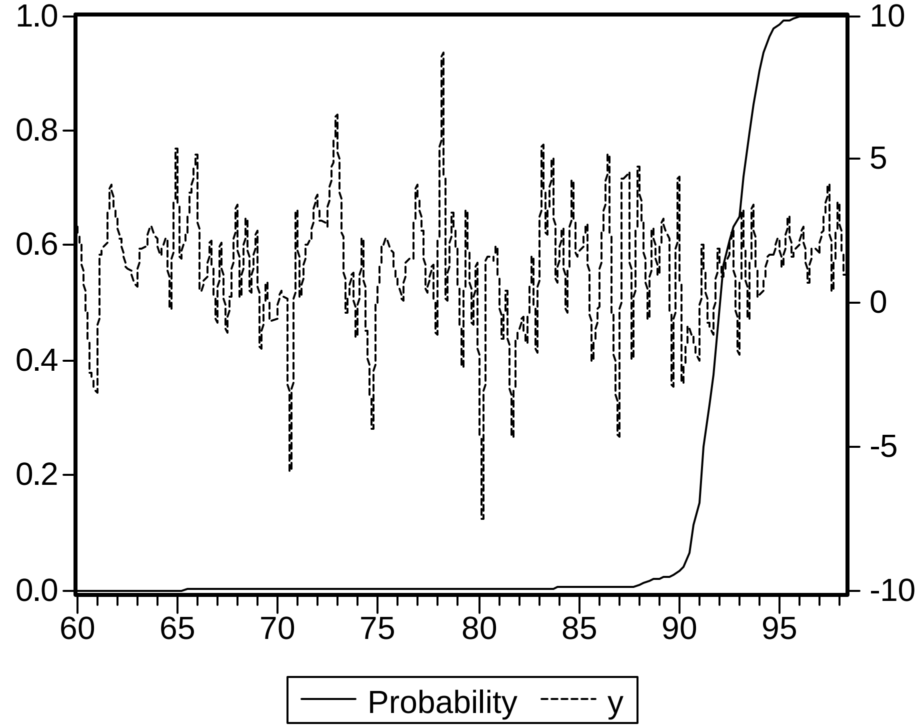

Figure 9.B. Posterior Distribution of Break Point: Durables Final Sales

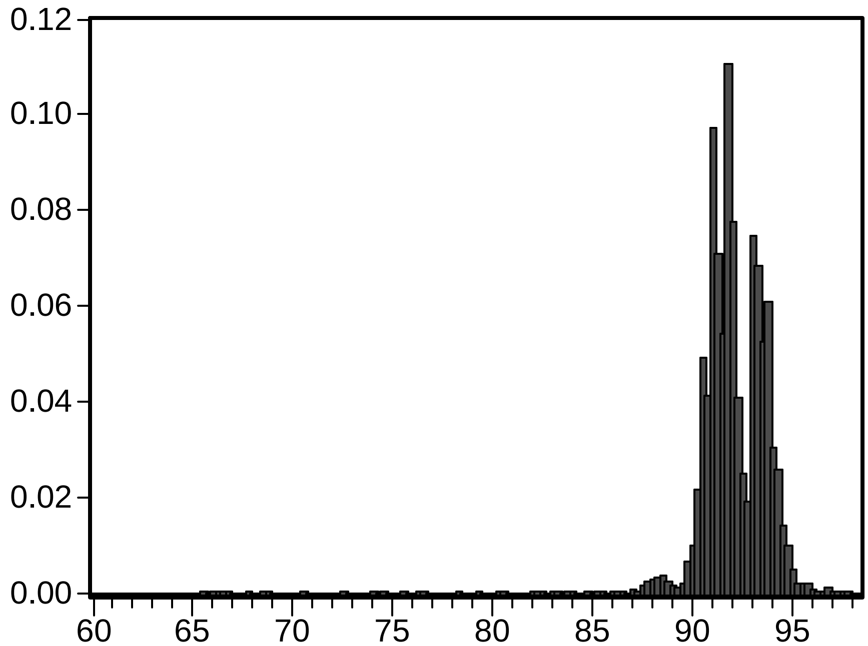

Figure 10.A. Final Sales of Domestic Production and Probability of Structural Break

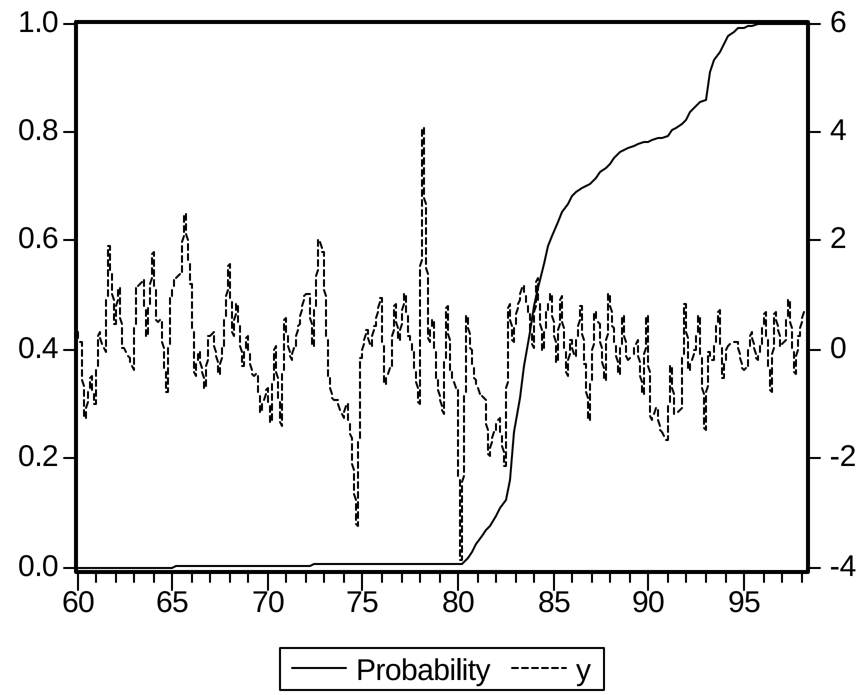

Figure 10.B. Posterior Distribution of Break Point: Final Sales of Domestic Production

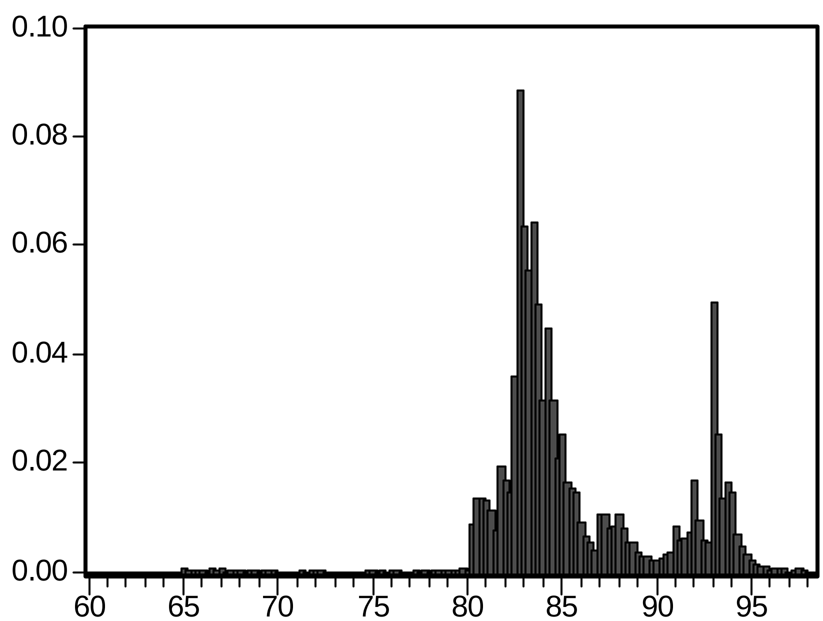

Figure 11.A. Probability of Structural Break in Inflation

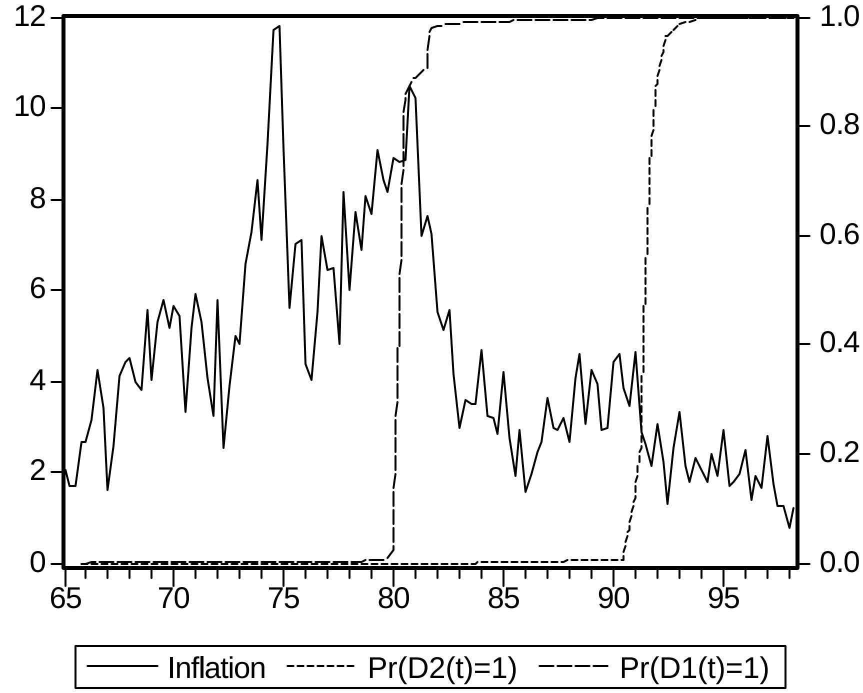

Figure 11.B. Posterior Distribution of Break Point for Inflation

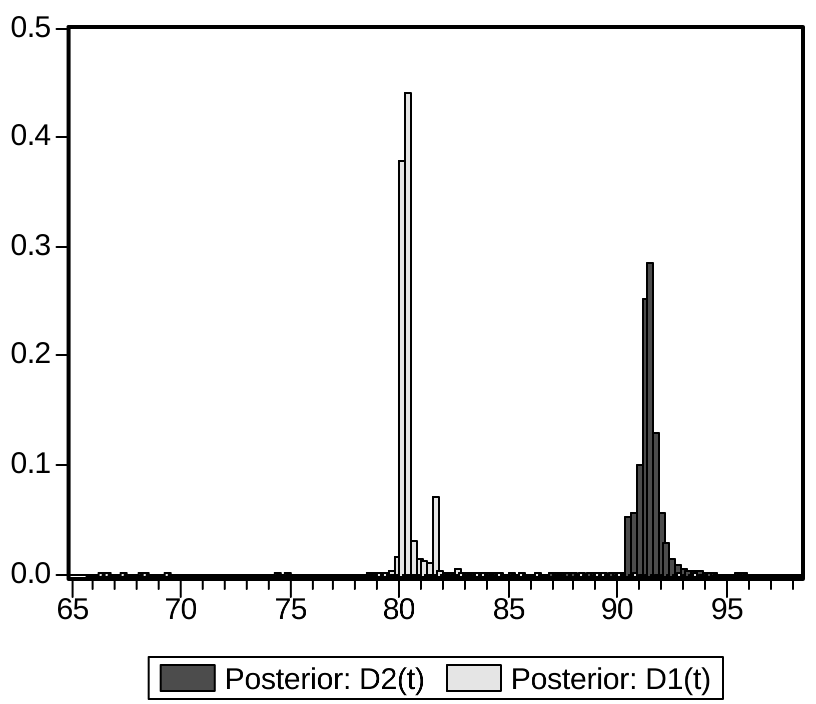

Figure 12.A. Probability of Structural Break in Ten Year Bond Yield

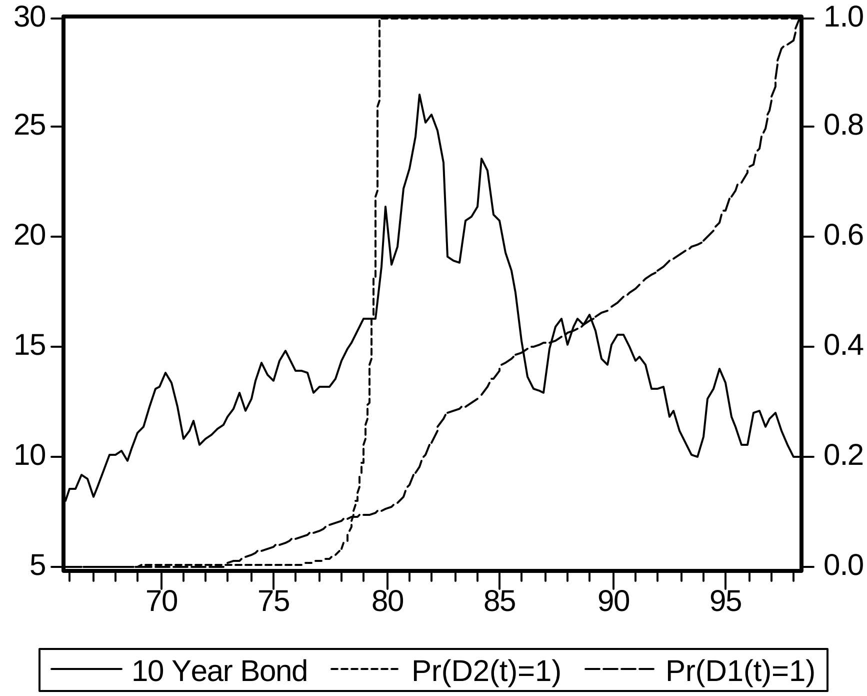

Figure 12.B. Posterior Distribution of Break Point for Ten Year Bond Yields

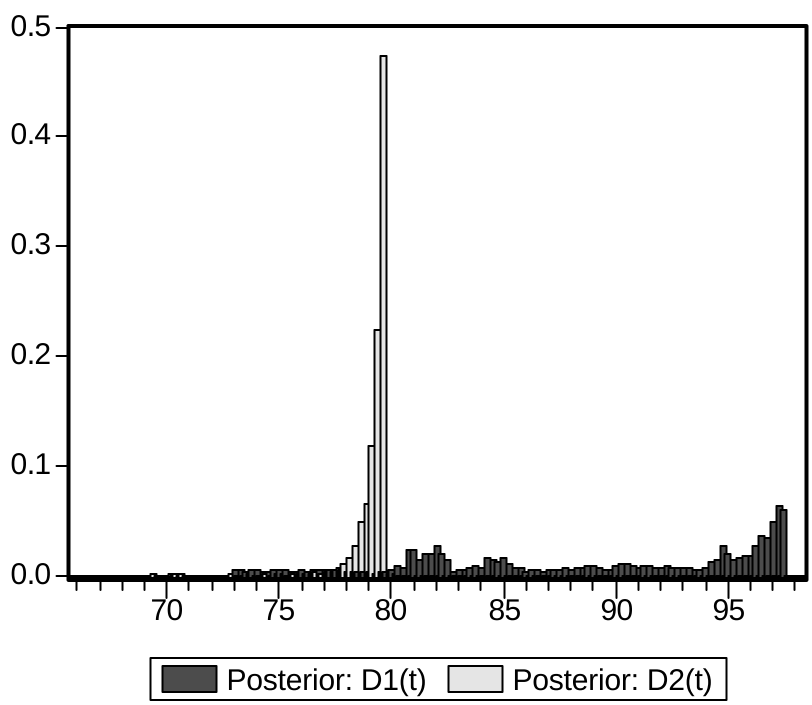

Figure 13.A. Probability of Structural Break in Federal Funds Rate

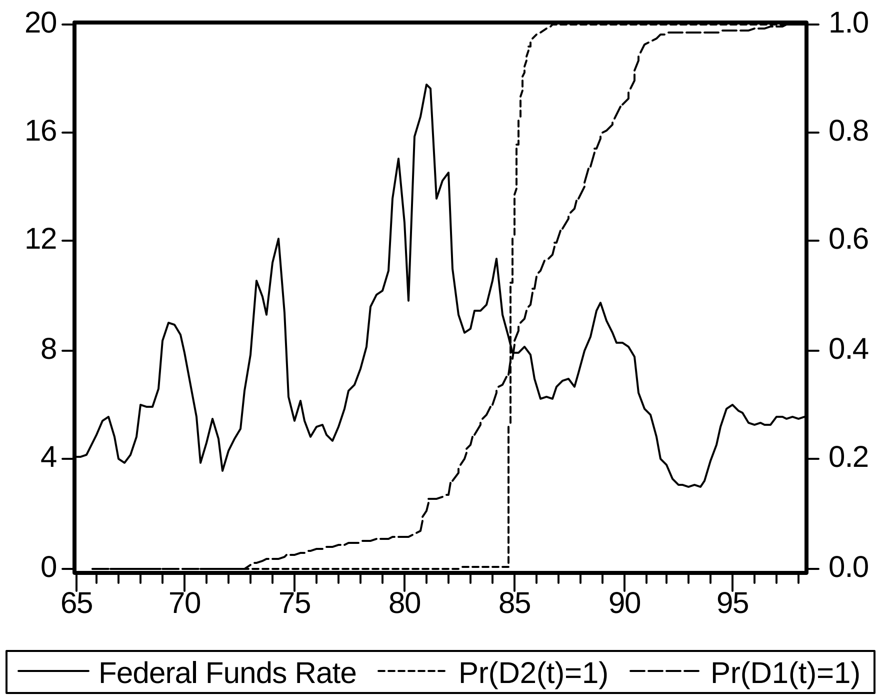

Figure 13.B. Posterior Distribution of Break Point for Federal Funds Rate