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Inflation Regimes and the Sources of Inflation Uncertainty

IN HIS 1976 NOBEL LECTURE, Milton Friedman argued that inflation uncertainty affects the trade-off between inflation and unemployment because inflation volatility and uncertainty "render market prices a less-efficient system for coordinating economic activity" (1977, p. 467). Friedman also suggested that uncertainty concerning the inflation regime may be the underlying source of the observed positive relation between inflation rates and volatility. He noted that the United States moved from a constant price regime to an inflationary regime in the post–World War II era. As a result, it may have taken several decades before people learned about the new regime and adjusted their expectations about whether the old regime would recur (see Klein 1975). Friedman saw regime uncertainty as an important source of inflation uncertainty. In this paper we examine Friedman's view by developing new measures of inflation uncertainty that account for the prospects of changing inflation regimes.

The existing empirical literature on inflation uncertainty has not explored the effects of changing inflation regimes. Early studies (see Okun 1971; Jaffee and Kleiman 1977; Logue and Willett 1976; Logue and Sweeney 1981; and Taylor 1981) used the variability of inflation as a proxy for inflation uncertainty which made it difficult to determine the underlying source of uncertainty. Similar problems beset the studies that used the dispersion of inflation forecasts gathered from the Michigan and Livingston surveys to proxy for inflation uncertainty (see Wachtel 1977; Carlson 1977; and Cukierman and Wachtel 1979). More recently, inflation uncertainty has been measured by the conditional variance of inflation modeled as an ARCH pro-

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cess (see Engle 1982, 1983; Holland 1984; Cosimano and Jansen 1988; and Jansen 1989). Generally, ARCH models provide estimates of how the conditional variance of inflation varies over time within a given structure. They therefore ignore the possibility of structural instability caused by changing regimes. One exception is the time-varying ARCH model developed by Evans (1991). This model allows for structural change as it occurs but does not account for the influence on uncertainty of possible future changes in regime.

This paper develops a model of the inflation process from which we can derive measures of inflation uncertainty that account for the prospects of changing inflation regimes. The model we develop is a Markov switching model that explains the changing time series behavior of inflation in the postwar era.[1] The model has at least two important implications for our understanding of inflation and inflation uncertainty. First, the switching model provides a framework for understanding the puzzling behavior of inflation forecasts in the postwar period. Second, the model allows us to estimate the extent to which uncertainty about future regime changes contributes to inflation uncertainty. These estimates can then be used to examine Friedman's conjecture that uncertainty concerning regime changes depresses real economic activity.

The recent history of U.S. inflation provides prima facie evidence on the importance of changing regimes. Figure 1 shows the twelve-month inflation rate in consumer prices and two common sources of inflation forecasts—the Livingston survey of professional forecasters and the Survey Research Center survey of individuals. The figure strongly suggests that there have been several distinct inflation regimes in the postwar period or apparent changes in the inflation process. An era of price stability began after the Korean War and lasted until the Vietnam War inflation began in the mid-1960s. The oil price shocks of the 1970s brought an era of high and volatile inflation that was followed by a gradual disinflation.

Figure 1 also shows that inflation expectations tend to lag changes in the structure so that forecast errors are very persistent and forecasts of inflation often appear to be biased. The systematic differences between forecasts of inflation and actual inflation have commonly been interpreted as evidence against rationality, in the sense that forecasters ignore relevant information [see, for example, Figlewski and Wachtel (1981) and Zarnowitz (1985)]. But this is not a very satisfying explanation in the absence of any reason why information is ignored. An alternative explanation, which has received less attention, is that forecasters are acting rationally, but face a complicated forecasting problem that makes systematic forecast errors unavoidable. Our Markov switching model shows how systematic forecast errors can arise rationally as the result of changing inflation regimes.

If forecasters are either anticipating a structural change in the inflation process or are learning about a past change, their forecast errors, although rational, may be serially correlated and systematically different from zero. Forecasts can appear bi-

1. Similar models have been estimated by Evans and Wachtel (1992b) for the Depression era and Evans and Lewis (1992) for the postwar period.

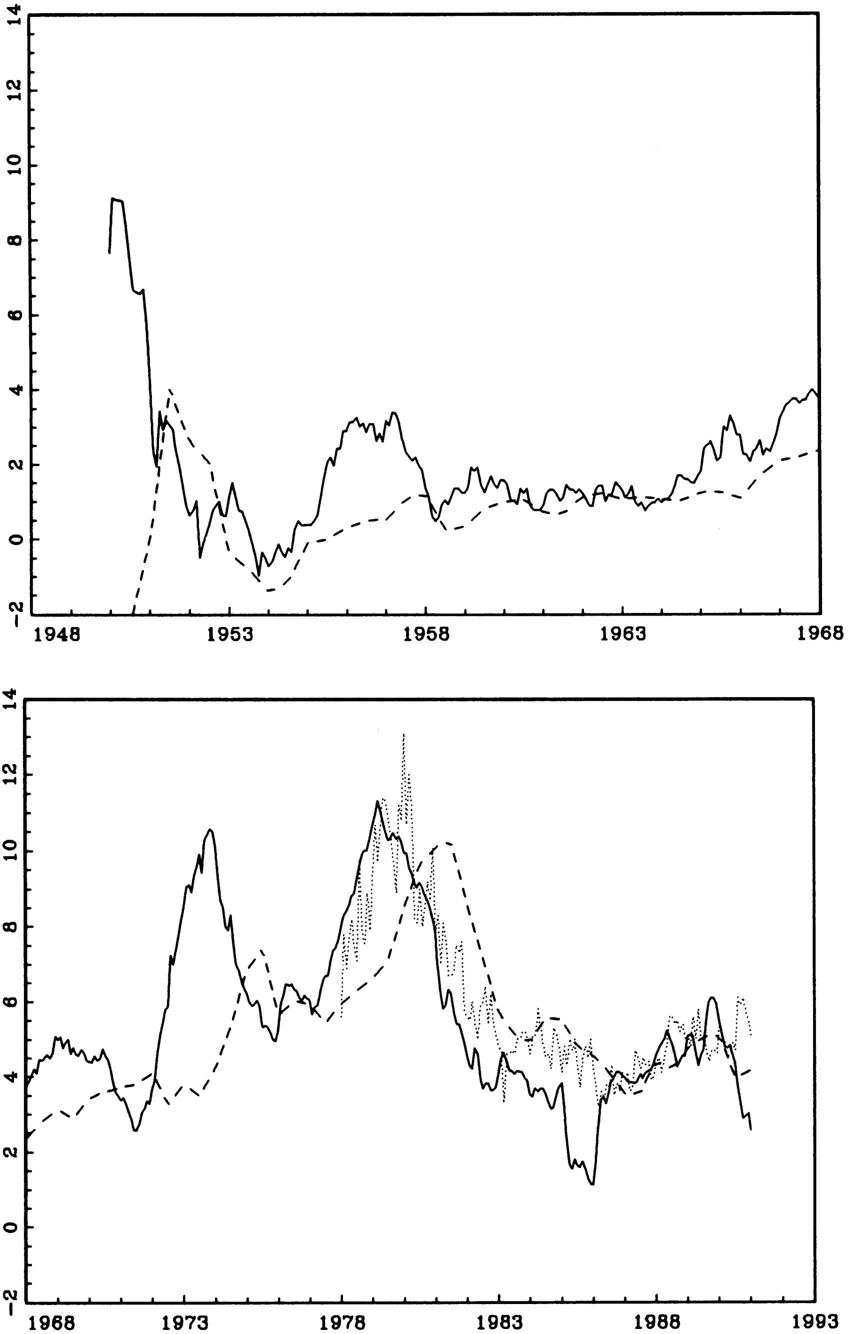


FIG. 1. Actual and Expected Inflation. Notes: ——— the twelve-month rate of inflation, — — — twelve-month Livingston survey, ... twelve-month SRC survey

ased when viewed with hindsight, a phenomenon known as ex post bias. For example, if inflation is in a high-inflation regime but forecasters perceive there to be a probability of a switch to a low-inflation regime, then their inflation forecasts will systematically underpredict inflation as long as the switch does not occur. Since regimes tend to change only infrequently, forecasts can appear to be biased for extended periods of time.

We shall show that the forecast errors from surveys of inflation forecasts tend to exhibit characteristics that are consistent with ex post bias. We will also show that the inflation forecasts from the Markov switching model are consistent with the survey data. Thus, the switching model provides an explanation for the systematic differences between surveys of inflation forecasts and actual inflation similar to those shown in Figure 1. This finding suggests that forecasters rationally account for the possibility of regime switches.

The Markov model provides us with an estimate of inflation uncertainty that can be decomposed into two components. First, there is a certainty equivalence component that ignores uncertainty about future inflation regimes and reflects the variance of future shocks to the inflation process. Second, there is uncertainty about future changes in the inflation regime. We compare our estimates of these components to other estimates of inflation uncertainty that have appeared in the literature. Interestingly, the survey measures of inflation uncertainty, based on the dispersion of forecasts, appear more closely associated to the regime uncertainty component than to the certainty equivalent component of inflation uncertainty. This result offers some insight into the source of dispersion in survey forecasts.

Finally, we use our estimates of inflation uncertainty to reexamine Friedman's hypothesis concerning the relationship between inflation uncertainty and real activity. We estimated vector autoregressive (VAR) models which include the unemployment rate, inflation, a measure of the stance of monetary policy, and the two components of inflation uncertainty. We find that uncertainty concerning the inflation regime, but not the certainty equivalence component of inflation uncertainty, has significant explanatory power in forecasting the unemployment rate. Variance decompositions show the percentage of the variance in the unemployment rate that are attributable to variations in inflation uncertainty. Our results indicate that more than one-fourth of the variance in twelve-quarter unemployment rate forecasts are due to uncertainty concerning regime changes in inflation forecasts with a two- or three-year horizon.

In summary, the Markov switching model for inflation provides us with a framework that explains many of the puzzling aspects of inflation and inflation forecasts. In particular, the model

- identifies regime changes in the postwar inflation process;
- provides a structure for inflation that is consistent with the behavior of survey forecasts and explains the behavior of forecast errors;
- provides an empirical measure of inflation uncertainty that accounts for regime uncertainty;
- shows that the regime uncertainty component of inflation uncertainty is an important influence on real economic activity.

The paper begins with an examination of the characteristics of inflation and various inflation forecasts. In section 2 we show how ex post bias can emerge. Section 3 presents the switching model and the estimates of inflation uncertainty. In section 4 we present VAR models that relate unemployment, interest rates, and inflation to inflation uncertainty.

1. CHARACTERISTICS OF INFLATION AND INFLATION FORECASTS

In this section we look at some of the time series characteristics of inflation and inflation forecasts. Our examination of the data and the patterns apparent in forecast errors will motivate our discussion of ex post bias and provide a basis for our specification of the switching model. We show that forecast errors tend to be serially correlated which is inconsistent with the standard rational expectations approach. However, serially correlated errors can occur with rational expectations when a change in regime is expected. We also show that there have been structural changes in the inflation process.

In order to examine inflation forecasts and forecast errors we use some of the survey data that are available in the United States for the postwar period. The surveys are usually collections of forecasts made by professional forecasters, although there is at least one random population survey that collects information about expected price change. The survey data indicate that inflation forecasts systematically lag behind the actual inflation rate. For example, increases in the inflation rate through the 1970s were largely unexpected, as was the disinflation of the 1980s. These characteristics led many economists to argue that the survey data could not possibly be an adequate representation of expected inflation rates because the expected systematic bias was inconsistent with rational expectations. However, we will see below that the survey data are consistent with rationality and the existence of ex post bias. We begin with a description of the survey data which is followed with an analysis of the properties of inflation and inflation forecasts.

Survey Measures of Expected Inflation

We examine data from the three best known sources of survey data on inflation expectations:

1. The Livingston survey was probably the first effort to systematically collect forecasts of the economy. It was started by a Philadelphia newspaper columnist, the late Joseph Livingston, in 1947 and is now maintained by the Federal Reserve Bank of Philadelphia. The survey is conducted twice a year (in December and June) and collects, among other things, six- and twelve-month forecasts of the CPI from approximately fifty different forecasters and business economists.[2]

2. Each survey requests forecasts of the level of the CPI in the following June and December. The calculation of the expected and corresponding actual inflation rates are based on Carlson's (1977) examination of the data and his approach has been adopted by the Philadelphia Fed. It can best be described by example. The December survey is mailed early in the month when the last announced number for the CPI is for October. Thus, the forecast for the CPI in the following June is used to calculate an eight-month expected inflation rate (from October to June).

2. The Survey Research Center (SRC) at the University of Michigan has included questions about price change in its consumer surveys since their inception in 1946. The SRC data are unique in that the survey uses a random population sample while the other surveys collect data from professional forecasters. The SRC survey has always asked questions about the rate of inflation but until May 1966, the questions were only qualitative (that is, will prices go up or down?). We use the monthly data which starts in 1978. The data are one-year-ahead expectations of the rate of change in prices in general which we take to represent the CPI.[3]

3. The Survey of Professional Forecasters (SPF) is the current name for the quarterly survey started at the end of 1968 by the ASA and the NBER. The survey is now conducted by the Federal Reserve Bank of Philadelphia. The survey collects forecasts of a variety of major economic indicators over various horizons. We use the forecasts of the level of the GNP Implicit Price Deflator. The one-quarter-ahead expected rate of inflation is based on the log difference between the survey forecasts of the following quarter and the survey forecasts of the current quarter level of the deflator.[4]

Characteristics of Inflation Forecasts

In Table 1, we show summary statistics for the three survey measures of the expected inflation rate and the corresponding actual inflation rates. The actual inflation rates are defined over the same horizon as the corresponding expectation and use the CPI with the SRC and Livingston data and the GNP deflator with the SPF data.[5] We write the one-period rate of inflation realized at time $t + j$ as $\pi_{t+j} \equiv (\log p_{t+j} - \log p_{t+j-1})$ where p_t is the price level and the corresponding rate of expected inflation given information available at t as $E_t\pi_{t+j}$.

All the survey measures of expected inflation exhibit a great deal of serial correlation, as does the actual inflation rate. The expected inflation rates drawn from professional forecasters (the Livingston and SPF data) are more persistent than the corresponding actual inflation rates. The SRC survey of individuals indicates that expected inflation is slightly less persistent than actual inflation.

The differences among the surveys in the persistence of the autocorrelations are due primarily to the differences in the forecast horizons. The SRC data includes considerable overlap since it consists of monthly observations on expectations with a twelve-month horizon. Thus, it is not surprising that ρ_{12} is .70. By comparison, the SPF data are quarterly observations with a one-quarter-ahead horizon; there is no overlap and the autocorrelations fade more quickly.

3. The data are based on telephone surveys of at least five hundred individuals and responses to the following questions:

During the next twelve months, do you think that prices in general will go up, or go down, or stay where they are now?

By about what percent do you expect prices to go up, on the average, during the next twelve months?

4. The survey also collects data on the expected rate of change in the CPI but these data began only in late 1981.

5. The data used are the non-seasonally adjusted CPI-U. Prior to 1983, we use the CPIX which utilizes the rental equivalence measure of housing costs that was introduced into the CPI-U at that time. The survey measures are the means of the participants' forecasts each period.

TABLE 1

SUMMARY STATISTICS

	Autocorrelations						Unit Root Tests	
	ρ_1	ρ_2	ρ_3	ρ_4	ρ_6	ρ_{12}	τ[1]	$\lambda(\tau)$[2]
SRC data, monthly, twelve-month CPI inflation, January 1978–January 1992								
Expected inflation	.928	.913	.884	.856	.839	.707	−0.993	−3.066
Actual inflation[3]	.987	.966	.943	.920	.876	.700	−2.111	−3.800
Livingston data, biannually, CPI inflation, June 1946–December 1991								
Six-month horizon								
Expected inflation	.843	.768	.683	.668	.569	.491	−1.417	−4.846
Actual inflation[3]	.786	.551	.365	.296	.429	.314	−1.584	−5.331
Twelve-month horizon								
Expected inflation	.869	.801	.722	.686	.592	.519	−0.825	−3.736
Actual inflation[3]	.863	.657	.477	.417	.452	.361	−1.743	−5.627
SPF data, quarterly, one-quarter GNP deflator, 1968.IV–1991.IV								
Expected inflation	.904	.826	.769	.693	.531	.165	−2.627	−3.801
Actual inflation[4]	.706	.706	.645	.585	.416	.195	−2.741	−3.714

NOTES: [1]Augmented Dickey-Fuller test for unit root allowing for a constant and a time trend. The test equation also allows for lags of the dependent variable to correct for serial correlation due to overlapping observations. The 5 percent and 1 percent critical values are −3.43 and −3.99.
[2]Zivot-Andrews minimum t-statistic for unit root. The 5 percent and 1 percent critical values are −4.80 and −5.80. Statistics less than the critical value indicate that the null of a unit root can be rejected.
[3]Inflation rates are calculated from the non-seasonally adjusted CPI-U. Prior to 1983, we use the CPIX which utilizes the rental equivalence measure of housing costs that was introduced into the CPI-U at that time.
[4]Inflation rates are calculated from the GNP deflator.

The table also includes Augmented Dickey-Fuller unit root tests. For all of the series shown, we are unable to reject the hypothesis of a unit root at the 5 percent significance level. The last column of the table presents minimum t-statistics developed by Zivot and Andrews (1992). These statistics allow us to ask whether a structural shift in the mean of the variables can make the process appear to contain a unit root.[6] The results are broadly similar to the Augmented Dickey-Fuller test statistics with the exception of the Livingston data.

The Livingston survey spans a much longer time period, forty-five years, than either the SRC data (fourteen years) or the SPF data (twenty-three years). Thus, it is not surprising that the presence of structural shifts may give rise to the appearances of a unit root. With the Livingston survey six-month expected inflation rate and the actual inflation rate corresponding to the Livingston survey data we can reject the hypothesis of a unit root at the 5 percent significance level. However, these rejections are due to the large movements in inflation during the late 1940s and early 1950s. When these years are excluded from the sample, we cannot reject the presence of a unit root.

Further evidence on the characteristics of inflation forecasts and the systematic relationships between inflation itself and the forecast errors (actual less expected inflation) is shown in Table 2. The table presents autocorrelations of the forecast er-

6. This issue was raised by Perron (1989). He found that for several macroeconomic series, the null hypothesis of a unit root process with drift and an exogenous break point could be rejected in favor of the alternative of a stationary process about a deterministic trend with an exogenous change in trend function. The Zivot and Andrews statistic tests the null hypothesis of a unit root against the alternative that the process is trend stationary with a break in the trend occurring at an unknown point in time.

TABLE 2

PROPERTIES OF FORECAST ERRORS

x_t	$s =$ 1	2	3	4	$\ell(3)$	$\ell(6)$
	Correlations of forecast error with x_t at lag s				ℓ–tests	
SRC data, monthly, January 1978–January 1992						
$\Delta\pi$	.481	.462	.362	.184		
$\Delta E\pi$	.043	−.034	−.035	−.001		
π-$E\pi$	.754	.666	.523	.407	.172	2.503
Livingston data, biannually, six-month horizon						
Full sample, June 1946–December 1991						
$\Delta\pi$	.259	.114	−.039	−.306		
$\Delta E\pi$	.243	−.148	.012	−.069		
π-$E\pi$	.361	.205	.036	.126	11.011	14.303
Subsample, June 1968–December 1991						
$\Delta\pi$	.264	.268	.173	−.118		
$\Delta E\pi$	.129	.051	−.015	−.022		
π-$E\pi$	.517	.352	.141	−.022	6.953	9.023
SPF data, quarterly, 1968.IV–1991.IV						
$\Delta\pi$	.460	.176	−.180	−.277		
$\Delta E\pi$	.147	−.164	.035	.149		
π-$E\pi$	.522	.270	.097	.211	8.338	11.239

NOTES: The Cumby-Huizinga (1992) $\ell(r)$-statistic tests the null hypothesis that the $v + 1$th to the $v + r$th autocorrelations are zero where v is the overlap in the survey data ($v = 11$ for SRC and $v = 0$ for the others). The statistic has a $\chi^2(r)$ distribution. The 5 percent and 1 percent critical values for $\ell(3)$ are 7.82 and 11.34, and for $\ell(6)$ are 12.59 and 16.81.

rors and simple correlations between the forecast errors and lagged changes in actual and expected inflation.

The first thing to note is that the forecast errors from all the survey series examined exhibit strong and persistent autocorrelations. These autocorrelations remain fairly strong for about one year.[7] The Cumby-Huizinga (1992) ℓ-statistics, $\ell(r)$, test for the presence of rth-order serial correlation beyond the lags implied by the forecast overlap. There is an eleven-month overlap for the SRC survey and none for the other two. That is, the SRC forecasts are monthly observations on a twelve-month forecast so an MA(11) in the errors would be expected. In this case, the $\ell(3)$ statistic tests the null hypothesis that the twelfth, thirteenth, and fourteenth autocorrelations are zero.[8] The null of no autocorrelation of the error terms is rejected for the Livingston and SPF data but not with the SRC survey.

Second, the cross-correlations of the forecast errors with the lagged changes in actual inflation ($\Delta\pi_{t-s}$) are very strong although they persist for only about half of a year. That is, when the inflation rate increases, the forecast errors tend to increase which means that expectations do not respond very rapidly to shocks to the inflation rate. The correlations between the forecast errors and lagged changes in the ex-

7. Note that the different data frequencies imply that the lag at a given s represents a different time horizon for each survey. For example, the lag at $s = 4$ represents four months for the SRC survey, two years for the Livingston, and one year for the SPF survey.

8. $\ell(r)$ has a χ^2 distribution with r degrees of freedom. The null of no autocorrelation is rejected if $\ell > \ell_c$. For the Livingston and SPF data there are no data overlaps and the statistic is equivalent to the Box-Pierce Q statistic.

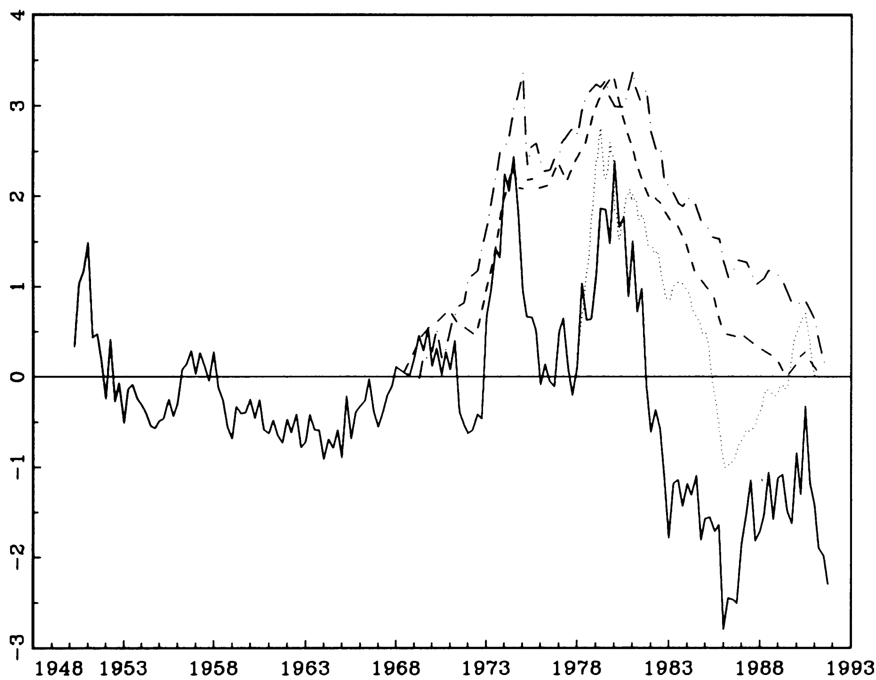


FIG. 2. Cumulated Survey Forecast Errors and Cusum Statistics. Notes: All series are standardized by subtracting the sample means and dividing the result by its standard deviation. The plotted series are: ——— Cusum statistics, — — — six-month Livingston survey, ... twelve-month SRC survey, and —.—.— 3-month SPF survey.

pected inflation rates show clearly that inflation forecasts tend not to respond very quickly to past errors.

Figure 2 allows us to examine the characteristics of the forecasts graphically. We show the cumulated sum of forecast errors which are analogous to the CUSUM statistics developed by Brown, Durbin, and Evans (1975). The figure shows the cumulative sums for three of the surveys[9] and also shows the CUSUM statistics calculated from a simple time series model for quarterly inflation. The time series model is an ARIMA(3,1,0) which allows for a unit root in the inflation rate and adequately captures all of the serial correlation in the first difference in the inflation rate when estimated over the whole sample period.[10] To make comparisons among the four series of cumulative errors easier, we have standardized all the plotted series by dividing each of the statistics by its sample standard deviation.

The figure shows that cumulative forecast errors and the CUSUM statistics share the same pattern. All the series increase steadily through the late 1960s and into the

9. We calculated the inflation rates at the same frequency as the survey data so that the forecast errors do not overlap.

10. The CUSUM statistics are calculated by cumulating the one-period-ahead forecast errors from rolling regression estimates of the time series model. They are comparable to the cumulative forecasts from the surveys.

TABLE 3

TESTS FOR STRUCTURAL STABILITY

Quarterly inflation (Consumer price index), 1947–91

$$\Delta\pi_t = \underset{(0.217)}{0.032} - \underset{(0.091)}{0.552}\,\Delta\pi_{t-1} - \underset{(0.105)}{0.443}\,\Delta\pi_{t-2} - \underset{(0.096)}{0.129}\,\Delta\pi_{t-3} + \epsilon_t$$

Residual Correlations	ρ_1	ρ_2	ρ_3	ρ_4
	0.011	0.037	0.015	−0.014
L-Statistics	L_1	L_2	L_3	L_4
	0.041	1.300**	1.351**	1.646*

Livingston six-month forecast, biannual data, June 1947–December 1991

$$\Delta\pi^e_t = \underset{(0.158)}{0.068} - \underset{(0.235)}{0.224}\,\Delta\pi^e_{t-1} - \underset{(0.167)}{0.107}\,\Delta\pi^e_{t-2} - \underset{(0.137)}{0.315}\,\Delta\pi^e_{t-3} + \epsilon_t$$

Residual Correlations	ρ_1	ρ_2	ρ_3	ρ_4
	0.009	−0.037	−0.037	−0.026
L-Statistics	L_1	L_2	L_3	L_4
	0.082	0.961**	1.053*	1.523*

SPF quarter-ahead forecast of GNP deflator, quarterly data, 1968.IV–1991.IV

$$\Delta\pi^e_t = \underset{(0.098)}{0.035} - \underset{(0.093)}{0.100}\,\Delta\pi^e_{t-1} - \underset{(0.960)}{0.106}\,\Delta\pi^e_{t-2} + \underset{(0.088)}{0.165}\,\Delta\pi^e_{t-3} + \epsilon_t$$

Residual Correlations	ρ_1	ρ_2	ρ_3	ρ_4
	−0.002	0.002	0.007	0.028
L-Statistics	L_1	L_2	L_3	L_4
	0.253	0.283	0.460	0.812

NOTES: The L-statistic (Hansen 1991) tests the null hypothesis of constant parameters against the alternative that the parameters follow a Martingale process. * and ** indicate that the null hypothesis of parameter constancy can be rejected at the 5 percent and at the 1 percent levels, respectively. ρ_i denotes the correlation at lag i.
L_1—test on the constant term (1 d.f.)
L_2—test on the variance of the residuals (1 d.f.)
L_3—test on constant term and the variance of the residuals (2 d.f.)
L_4—test on the constant term, the variance of the residuals, and the AR parameters (5 d.f.)

1970s as inflation accelerated. Forecasts of inflation in this period tended to systematically underestimate realized inflation. Between 1974 and 1980 the CUSUM statistics calculated from the rolling regression estimates of the time series model swing down and then up, while the cumulative forecast errors from the surveys remain fairly stable. After 1980 all four series trend sharply downward indicating that the forecasts of inflation were systematically above the realized inflation rate.

The large and systematic variations in the CUSUM statistics suggest that there are structural changes in the inflation process. To test parameter constancy more formally, we used the L-statistic proposed by Hansen (1991). This statistic allows us to test the null hypothesis of parameter stability against the alternative hypothesis that the parameters follow a martingale process. The upper panel of Table 3 report the results of these tests based on the estimates of an ARIMA(3,1,0) model for quarterly inflation estimated over the whole sample. As the residual autocorrelations ρ_i show, this simple model does a reasonably good job of capturing the predictable variations in inflation.

The table reports four L-statistics that test the stability of different combinations of the model's parameters. These statistics reveal that we can reject the null hypothesis of no structural instability in at least the variance and the autoregressive parameters at the 5 percent significance level.[11]

The finding of instability in the inflation process raises the possibility that the time series properties of expectations have also changed. Under the standard rational expectations assumption that forecast errors are white noise, we would expect any changes in the persistence of actual inflation to be mirrored by changes in the persistence of expected inflation. If, on the other hand, changes in the inflation process were not matched by changes in the process for expectations (for reasons we discuss below), the forecast errors would be serially correlated. Thus, the large swings in the cumulative residuals shown in Figure 1 could result from instabilities in the process for inflation coupled with relative stability in the process for expectations.

The middle and lower panels of Table 3 report the results of stability tests based on simple time series models for the Livingston and SPF surveys. It appears that both surveys can be modeled as ARIMA(3,1,0) process; the first four autocorrelations of the residuals are extremely small. The L-statistics indicate that there is parameter instability in the model for the Livingston forecasts but not the model for the SPF. However, since the SPF model is estimated over a much shorter time period, the failure to find evidence of instability is not too surprising.

To summarize, the results in this section show that data on inflationary expectations from different surveys have similar characteristics. In particular, the forecast errors implied by these expectations are both serially correlated and correlated with lagged inflation. These results are inconsistent with the standard rational expectations assumptions that (nonoverlapping) forecast errors should be uncorrelated with current information. We have also shown that the pattern of forecast errors based on survey data is broadly consistent with the pattern made by (dynamic) forecasts based on a simple time series model. Our stability tests reveal structural changes in the inflation process as a possible explanation for these results. In the next section we examine why rational agents are likely to make systematic forecast errors similar to those we have observed.

2. THE FORMATION OF INFLATIONARY EXPECTATIONS

There are two explanations for the systematic differences between forecasts of inflation and actual inflation. First, forecasts may not be made rationally, in the sense that forecasters ignore relevant information. The systematic deviations of survey forecasts from actual inflation have been interpreted in these terms by Figlewski and Wachtel (1981) and Zarnowitz (1985) among others. However, this explanation

11. Even though there is no direct evidence of shifts in the constant, Hansen (1991) finds in Monte Carlo experiments that it is difficult to test the stability of one set of parameters if another subset of parameters is shifting over time. Therefore, shifts in autoregressive parameters or constants may show up as apparent shifts in the variances.

is not very satisfying in the absence of any reason to ignore relevant information. The second explanation is that forecasters may be acting rationally, but face a complicated forecasting problem that makes systematic forecast errors unavoidable.[12] In particular, if forecasters are either anticipating a structural change in the inflation process or are learning about a past change, their forecast errors, although rational, may be serially correlated and systematically different from zero.

Since there appears to be evidence of structural instability in the actual inflation process, this second explanation deserves examination. Below we show how the perceived presence of switches in the inflation process affect forecasts of inflation and contribute to inflation uncertainty. Expectations of future changes in the inflation process or learning about past changes in the process can give rise to rational forecasts that are systematically wrong.[13] This is the phenomenon knowns ex post bias. In subsequent sections we will specify and estimate a model with these characteristics that allows us to test for their presence.

Forecasting in the Presence of Process Switching

The implications of switches in the inflation process are best described with the aid of a simple example. Suppose that the process for the inflation rate switches between two processes and that the switches are governed by the unobservable state variable, s_t, that takes on the value of one or zero. Let $\lambda_t = Pr(s_{t+1} = 1|\Omega_t)$ be the probability that the one-period rate of inflation, π_t, is governed by the process in state one given the information available to agents at t, Ω_t. The expected rate of inflation is then

$$E_t\pi_{t+1} \equiv E[\pi_{t+1}|\Omega_t] = \lambda_t\, E[\pi_{t+1}|s_{t+1} = 1, \Omega_t] + (1 - \lambda_t)\, E[\pi_{t+1}|s_{t+1} = 0, \Omega_t] \,. \tag{1}$$

Equation (1) states that the expected future inflation rate is a weighted average of the expectations conditional upon the process in state one, $E[\pi_{t+1}|s_{t+1} = 1, \Omega_t]$, and state zero, $E[\pi_{t+1}|s_{t+1} = 0, \Omega_t]$, where the weights are the probabilities of being in the respective states. Expectations conditional on a particular state can arise when agents are (i) learning about a past change in the inflation process, and (ii) anticipating future shifts in the inflation process.

(i) After a change in the inflation process, agents may require time to learn about the new process. For example, suppose that the process for inflation changed from the old, state-zero, process to the state-one process, and that agents are unsure that the

12. A third possibility is that the apparent irrationality of the survey data indicates that the surveys are not an adequate representation of the expectations of economic agents. This possibility was considered by many of the first analysts to examine the data, for example Pesando (1975). However, as we have shown, the systematic properties of the forecast errors appear in different surveys and also in time series forecasts of inflation. Thus, we conclude that they are due to something other than inadequacies of the survey data.

13. The impact of future discrete changes on expectational errors was first pointed out by Rogoff (1980). Lewis (1991) investigated their empirical importance in a study of nominal interest rates. The effects of learning on forecast errors after changes in policy are described in Lewis (1989).

change has occurred. They would observe the inflation rate following the suspected change and try to learn whether the process has indeed changed. If they learn in a Bayesian way, they begin with a prior probability of a change and then update this probability based upon subsequent observations of inflation. As they learn, agents weight forecasts conditional upon each regime by their assessed probability that the old or new process is currently generating inflation. Under these circumstances expected inflation will be identified by equation (1) where λ_t denotes the probability that inflation is following the state-one process in $t + 1$. With sufficient observations from the new process, agents will learn that inflation is in fact following the state-one process and λ_t will converge to one.

(ii) If agents believe that the inflation process may change in the future, their expectations of future inflation will incorporate expectations conditional upon the alternative inflation process. For example, suppose that inflation is following the state-zero process, but agents anticipate that the process will switch to the state-one process. In this case, expectations will take the form of equation (1) where λ_t is now the probability of a switch to the new process. Thus, expected inflation is the probability-weighted average of expected inflation conditional upon the current process and upon the process anticipated if a switch occurs. Notice that in this case agents understand fully the current inflation process (and hence do not need to learn), but believe that this process may change in the future.

We now examine the implications of expectations that are influenced by either learning about past shifts in the inflation process or by anticipating future shifts in the process. We assume that there are two inflation processes so that expectations are described by equation (1). The major implication of this model is that rationally formed expectations can be biased when viewed with the benefit of hindsight.

To show this, let us assume that inflation currently follows the state-one process. In this case, the ex post forecast error (that is, the difference between actual inflation and the forecast given in equation (1)) is

$$\pi_{t+1} - E[\pi_{t+1}|\Omega_t] = (\pi_{t+1} - E[\pi_{t+1}|s_{t+1} = 1, \Omega_t]) \\ + (1 - \lambda_t)(E[\pi_{t+1}|s_{t+1} = 1, \Omega_t] - E[\pi_{t+1}|s_{t+1} = 0, \Omega_t]) \,. \tag{2}$$

The first term on the right-hand side has a mean of zero because we have assumed that inflation is following the state-one process in period $t + 1$. In other words, the observed inflation rate is uncorrelated with the forecasts that were conditioned upon the state-one process, that is, $E[\pi_{t+1} - E[\pi_{t+1}|s_{t+1} = 1, \Omega_t]|\Omega_t] = 0$. However, if agents place some weight on the possibility that inflation may follow the state-zero process in period $t + 1$, then the second term on the right-hand side of (2) will not have a mean of zero. In this case, $(1 - \lambda_t) = Pr(s_{t+1} = 0|\Omega_t) > 0$ and the second term will not have a mean of zero as long as the expectations conditional on the two states differ. In general, the difference between the two expectations may be correlated with current information, Ω_t, including past forecast errors. This means that the forecasts, $E[\pi_{t+1}|\Omega_t]$, will appear biased when viewed ex post even though agents are using all available information efficiently in making their forecasts.

Ex post bias occurs when inflation follows a particular process (state one in the example above) and expectations incorporate the possibility that the process will switch. As long as the actual process continues in state one and the possibility of a switch to state zero persists, rational forecasts will be biased.

The characteristics of the forecast errors from both the survey data and the time series model for inflation are consistent with the presence of ex post bias. That is, the forecast errors have nonzero means and follow systematic patterns. Figures 1 and 2 indicate that periods of consistent over- or underprediction of the inflation rate can continue for many years. Ex post bias can persist for long periods of time.

The behavior of the Livingston survey in the early postwar years provides an example of forecast errors that are probably due to ex post bias. A large number of the professional forecasters in the survey anticipated that a postwar deflation would emerge. The expectation of a switch to a deflationary regime persisted well into the 1950s and led to systematic underpredicting of the postwar inflation (see Figure 1). These errors are probably not due to irrationality. Instead they probably reflect the possibility of a switch to a deflationary regime which was a consequence of very long-term memory of the post–World War I deflation. As that experience became less relevant, the probability of a switch to a deflationary regime, λ_t, changed. In the 1950s the Livingston survey forecasts the inflation rate without any persistent errors.

The model of ex post bias takes the probability λ_t to be time varying. If λ_t were constant throughout, then the estimated process for the inflation rate should be stable. However, the results in Table 2 suggest instability in the process for expected inflation. This finding is consistent with changes in the probability λ_t in equation (1) and our interpretations of the model.

Measuring Inflation Uncertainty in the Presence of Process Switching

We define inflation uncertainty as the conditional variance of inflation that will be affected by the possibility of switches in the inflation process. The effects of process switching on the conditional variance are shown in equation (3). When the inflation rate can switch between states, the variance of quarterly inflation k periods ahead can be written as

$$Var(\pi_{t+k}|\Omega_t) = E\{Var(\pi_{t+k}|\Omega_t, s_{t+k})|\Omega_t\} + Var\{E(\pi_{t+k}|\Omega_t, s_{t+k})|\Omega_t\} . \qquad (3)$$

The first term on the right is the expectation over the different states of the variance of inflation given that you know the state that the process will be in at $t + k$. The second term is the conditional variance of expected inflation when the state is unknown where expected inflation is conditioned on knowledge of the process at $t + k$.

If expectations are independent of s_{t+k}, then the second term in equation (3) is equal to zero, that is, $Var\{E(\pi_{t+k}|\Omega_t, s_{t+k})|\Omega_t\} = 0$.[14] In this case uncertainty is measured by the first term in (3) and the only source of uncertainty is uncertainty

14. If inflation follows a single process, then s_{t+k} takes a single value and $Var\{E(\pi_{t+k}|\Omega_t,s_{t+k})|\Omega_t\} = 0$. When there is only one state, the first term in (3) degenerates to Var $(\pi_{t+k}|\Omega_t)$.

originating from the realizations of future inflation shocks between t and $t + k$. We refer to the first term in (3) as the "certainty equivalent" component of the variance.

If inflation expectations depend upon the future states s_{t+k}, $Var\{E(\pi_{t+k}|\Omega_t, s_{t+k})|\Omega_t\} > 0$.[15] We call the second term in equation (3) the "regime uncertainty" component of the variance of inflation because it identifies the effects of future changes in the inflation process. Thus, in general the variance of inflation comprises two components: the certainty equivalent component, and the regime uncertainty component.

Time series models of the inflation process, such as the ARCH model introduced by Engle (1982, 1983), have been used to estimate inflation uncertainty. However, these models assume that inflation follows a single process and that uncertainty is due only to shocks to the inflation process. Equation (3) makes clear that estimates of inflation uncertainty derived from time series models that ignore the possibility of shifts in the inflation process will tend to underestimate the degree of inflation uncertainty because they identify only the certainty equivalent component. More recent ARCH models have allowed for structural change in the inflation process. In particular, Evans (1991) and Evans and Wachtel (1992) estimate ARCH models in which the process for the conditional mean have time-varying coefficients. These models account for the influence of learning about past shifts in the inflation process on inflation uncertainty but still fail to account for the effect of anticipated future shifts.

The second line of equation (2) shows that in situations where people anticipate future shifts in the inflation process, ex post bias will be present in the forecast errors (that is, when $\lambda_t < 1$). Hence, if the systematic patterns in forecast errors are symptomatic of ex post bias, there is good reason to suspect that conventional ARCH estimates of inflation uncertainty (based only on the certainty equivalent component) may underestimate the true degree of inflation uncertainty.

In the next section we specify a time series model for inflation that allows for switches in the process. The conditional variance of inflation from this model includes both certainty equivalent and regime uncertainty components. Thus we will be able to show how the effects of process switches have contributed to inflation uncertainty during the postwar period.

3. A MARKOV SWITCHING MODEL FOR INFLATION

In this section we present a Markov switching model for inflation that allows for switches in the inflation process. We show that rational forecasts derived from this model exhibit ex post bias and are consistent with the survey measures of expected inflation examined above. We then use the model to derive estimates of inflation uncertainty that account for the shifts in the inflation process.

Model Estimates

The specification of the switching model that we estimate is suggested by the time series characteristics of inflation. The model allows for two inflation processes, an

15. Obviously, we are implicitly assuming that s_{t+k} follows a stochastic process.

AR(1) process and a random walk without drift. One process has a unit root because the results in Table 1 indicate that there is a unit root in quarterly inflation, π_t, in the past thirty-five years. The other process is a simple autoregressive model that allows for the observed persistence of inflation in the absence of the unit root. The model is given by

$$\pi_t = \pi_{1,t}\, s_t + \pi_{0,t}\,(1 - s_t) \tag{4}$$

where

$$\pi_{1,t} = \pi_{1,t-1} + v_{1,t} \qquad v_{1,t} \sim N(0,\sigma_1^2)\ ,$$

and

$$\pi_{0,t} = \alpha_0 + \alpha_1\, \pi_{0,t-1} + v_{0,t} \qquad v_{0,t} \sim N(0,\sigma_0^2)\ .$$

Switches between the two processes are governed by the state variable s_t that follows a first-order Markov process:

$$\begin{aligned} &Pr(s_t = 1|s_{t-1} = 1) = q_1 \qquad &&Pr(s_t = 0|s_{t-1} = 1) = 1 - q_1 \\ &Pr(s_t = 0|s_{t-1} = 0) = q_0 \qquad &&Pr(s_t = 1|s_{t-1} = 0) = 1 - q_0\ . \end{aligned} \tag{5}$$

The specification in (4) differs slightly from the Markov switching model developed by Hamilton (1990). Our model allows for discrete changes in the inflation process because the random walk and autoregressive processes depend on the lagged values of inflation in the respective processes. To show this, rewrite (4) as

$$\begin{aligned} \pi_t = {} & s_t\, \pi_{t-1} + (1 - s_t)(\alpha_0 + \alpha_1\, \pi_{t-1}) + s_t\, v_{1,t} + (1 - s_t)\, v_{0,t} \\ & + \phi[s_t(1 - s_{t-1}) - \alpha_1\,(1 - s_t)s_{t-1}]\,(\pi_{1,t-1} - \pi_{0,t-1}) \end{aligned}$$

where $\phi = 1$. When the inflation process switches ($s_t = 0$ and $s_{t-1} = 1$ or vice versa), there can be a discrete jump in the inflation rate. In Hamilton's model, $\phi = 0$ and only the dynamic of the inflation process change when the process shifts. Our model with $\phi = 1$ appears to better capture the nature of the structural shifts. Using the parameter estimates in Table 4 below, we computed the p-value of a one-sided test that $\phi = 0$ to be 0.095, suggesting the discrete shifts were an important characteristic of the data.

Maximum likelihood estimates of the model are shown in Table 4.[16] All the parameters are much larger than their standard errors. The unconditional mean of the inflation rate from the autoregressive process is 1.9 percent at annual rates. The variance of the disturbances is much larger for the random walk than for the autoregressive process. The estimates of the transition probabilities, that govern the dy-

16. The estimates were obtained using a modified version of the filtering algorithm developed by Hamilton (1990). Details of this procedure are described in Evans and Wachtel (1992b).

TABLE 4

ESTIMATES OF MARKOV SWITCHING MODEL FOR QUARTERLY INFLATION, 1955–91

$$\pi_t = \pi_{1t}\, s_t + \pi_{0t}(1 - s_t)$$

$$\pi_{1t} = \pi_{1t-1} + v_{1t} \qquad \sigma^2_{v1} = \underset{(1.299)}{6.253}$$

$$\pi_{0t} = \underset{(0.281)}{0.807} + \underset{(0.135)}{0.577}\,\pi_{0t-1} + v_{0t} \qquad \sigma^2_{vo} = \underset{(0.423)}{2.544}$$

$$\Pr(s_t = 1 \mid s_{t-1} = 1) = \underset{(0.024)}{0.979}$$

$$\Pr(s_t = 0 \mid s_{t-1} = 0) = \underset{(0.016)}{0.985}$$

LM Specification Tests

	T_1	T_2	T_3	T_4
χ^2	2.258	0.106	0.359	0.519
Significance	(0.133)	(0.744)	(0.549)	(0.471)

NOTES: LM specification tests:
T_1—for first-order serial correlation in v_1
T_2—for first-order serial correlation in v_0
T_3—for first-order ARCH in v_1
T_4—for first-order ARCH in v_0

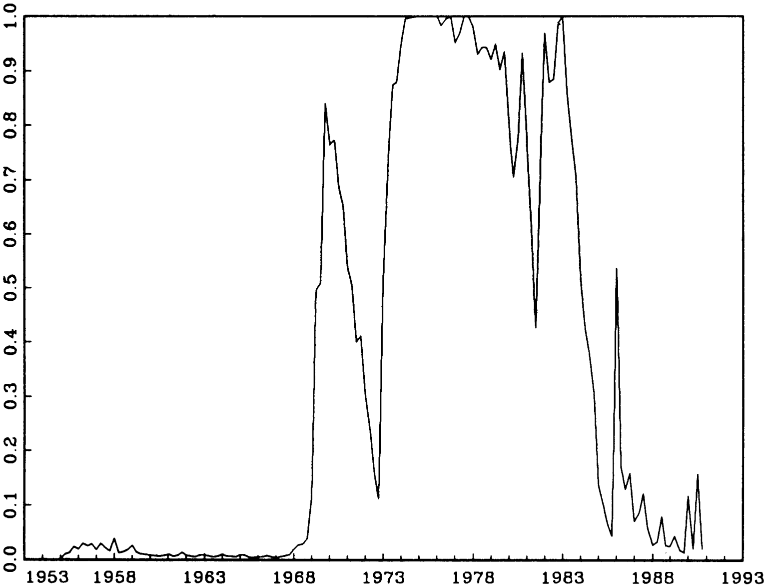
namics of s_t, indicate that both states are characterized by a great deal of persistence. The probability of remaining in either state from one quarter to the next is about 98 percent.

Table 4 also shows the results of a number of specification tests. The first two are Lagrange multiplier (LM) tests for first-order autocorrelation in the residuals of each process. In both cases we fail to reject the restriction of no serial correlation. The second two LM statistics test for conditional heteroskedasticity in the residual from each process. Again, the restrictions implying the absence of ARCH cannot be rejected in either case.

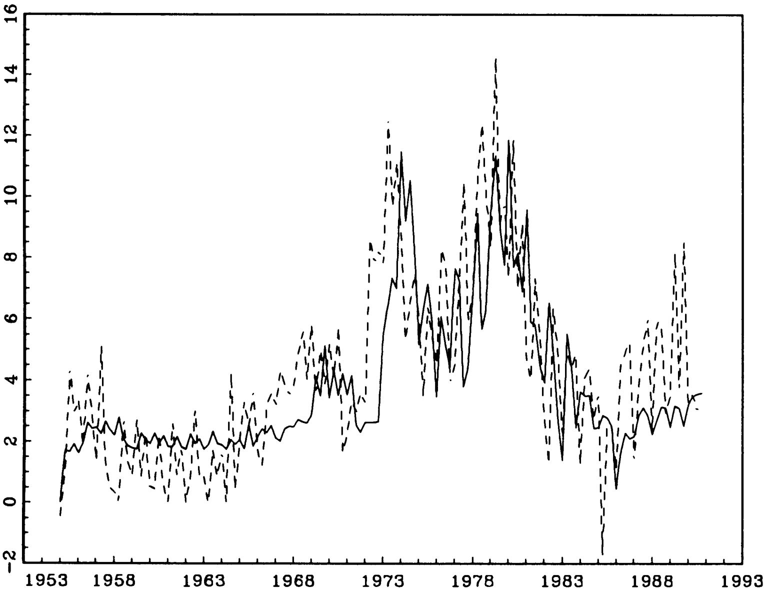
Figure 3 shows some of the implications of the estimated model. The upper panel plots the probability of being in the unit root or random walk state ($s_t = 1$). It is extremely small from the start of the sample in 1955 until 1970 when the inflation process changes dramatically. In the late 1970s the probability hovers near 100 percent and it does not fall appreciably until 1985. It is interesting to note that the sharp movements in the probability of being in a particular state change at about the same time as there are major swings in the CUSUM statistics shown in Figure 2. This suggests that the Markov model identifies the shifts in the inflation process that account for the systematic pattern in forecasts errors implied by the simple ARIMA(3,1,0).

The general k-period ahead forecast is calculated as

$$\begin{aligned} E^M[\pi_{t+k}|\Omega_t] &= E[\pi_{1,t+k}|\Omega_t]Pr(s_{t+k} = 1|\Omega_t) \\ &\quad + E[\pi_{0,t+k}|\Omega_t][1 - Pr(s_{t+k} = 1|\Omega_t)] \\ &= \pi_{1,t}Pr(s_{t+k}|\Omega_t) \\ &\quad + [\alpha_0(1 - \alpha_1^k)/(1 - \alpha_1) + \alpha_1^k\pi_{0,t}][1 - Pr(s_{t+k} = 1|\Omega_t)] \end{aligned} \tag{6}$$



Panel A



Panel B

FIG. 3. Markov Estimates of Quarterly Inflation. Notes: Panel A plots the probability of being in unit root state (s_t = 1). Panel B plots Markov forecasts of quarterly inflation one year ahead, $E_t\,\pi_{t+4}$, ———; and actual quarterly inflation one year ahead, π_{t+4}, — — —.

where

$$Pr(s_{t+k} = 1|\Omega_t) = [1 \;\; 0] \begin{bmatrix} q_1 & 1 - q_1 \\ 1 - q_0 & q_0 \end{bmatrix}^k \begin{bmatrix} Pr(s_t = 1|\Omega_t) \\ Pr(s_t = 0|\Omega_t) \end{bmatrix}$$

The Markov forecasts of quarterly inflation one year ahead, $E^M[\pi_{t+4}|\Omega_t]$, are shown in the lower panel of Figure 3, along with the corresponding actual level, π_{t+4}.[17] The figure shows that in the late 1950s the forecasts tended to exceed the very modest actual inflation rates. When inflation accelerated in the 1960s, the forecasts consistently lagged behind. Similarly, when disinflation set in during the 1980s inflation forecasts tended to exceed the actual inflation rate. The survey data show similar patterns except that most forecasts of inflation show substantially more underprediction of the disinflation of the 1980s.[18]

Consistency of Survey Forecasts and Switching Model

A formal comparison of the survey data and the forecasts from the Markov switching model provides us with a way of interpreting both sets of forecasts. If survey participants rationally accounted for the possibility of changing regimes when forming their forecasts, and the regimes correspond to those identified by the Markov model, forecasts derived from the Markov model should be consistent with the survey forecasts. The systematic errors in survey data on inflation forecasts could then be interpreted as a manifestation of ex post bias. We could also be confident that the measures of inflation uncertainty derived from our Markov model account for the possibility of regime switches in a manner consistent with the survey data.

We examine the consistency of the Livingston survey forecasts with the Markov forecasts in two ways.[19] First, we test whether the Markov model and survey forecasts systematically differ from one another. Second, we compare the likelihood of future process switches implied by the survey forecasts with the transition probabilities estimated from the Markov model.

To test whether the Markov forecasts and the Livingston survey forecasts differ systematically, we need to define the forecasts over the same horizon. The Livingston survey reports inflation forecasts with both two- and four-quarter horizons which will be denoted as $E^{Liv}[\pi^2_{t+2}]$ and $E^{Liv}[\pi^4_{t+4}]$, respectively. The corresponding Markov forecasts are given by $E^M[\pi^2_{t+2}|\Omega_t] = \frac{1}{2}(E^M[\pi_{t+2}|\Omega_t] + E^M[\pi_{t+1}|\Omega_t])$ and $E^M[\pi^4_{t+4}|\Omega_t] = \frac{1}{4}(E^M[\pi_{t+4}|\Omega_t] + E^M[\pi_{t+3}|\Omega_t] + E^M[\pi_{t+2}|\Omega_t] + E^M[\pi_{t+1}|\Omega_t])$ where the quarterly Markov forecasts, $E^M[\pi_{t+j}|\Omega_t]$, are calculated from (6).

17. We show forecasts with a one-year-ahead horizon in order to give more emphasis to the role of uncertainty concerning the switch in process. One-quarter-ahead forecasts would track the inflation rate very closely because the probability of changing regime in the next quarter is extremely small.

18. One reason for the differences is that the Markov forecasts shown here are within sample forecasts that have a zero mean by construction.

19. We use the Livingston Survey forecasts because they extend over the longest sample period. As we have shown, these forecasts are similar to the other surveys.

TABLE 5

CONSISTENCY TESTS BETWEEN MARKOV AND LIVINGSTON INFLATION FORECASTS, 1955–91

Extended Model

$$E^{Liv}[\pi^2_{t+2}|\Omega_t] = E^M[\pi^2_{t+2}|\Omega_t] + \epsilon_{2,t}$$
$$E^{Liv}[\pi^4_{t+4}|\Omega_t] = E^M[\pi^4_{t+4}|\Omega_t] + \epsilon_{4,t}$$

$\sigma^2_{\epsilon 2} = 8.984$ (1.478)	$\sigma^2_{\epsilon 4} = 9.304$ (1.530)	$\sigma^2_{\epsilon 2,\epsilon 4} = 9.052$ (1.496)

LM Specification Tests for Serial Correlation

Tests for Serial Correlation in	ϵ_2	ϵ_4
χ^2	0.518	1.155
Significance	(0.472)	(0.283)

LM Specification Tests for Equality of Ex Ante and Ex Post Transition Probabilities

Tests for probability	$\Pr(s_t = 1\|s_{t-1} = 1)$ $q_1 = q_1^*$	$\Pr(s_t = 0\|s_{t-1} = 0)$ $q_0 = q_0^*$
χ^2	3.231	0.409
Significance	(0.072)	(0.522)

To compare the Livingston forecasts to Markov forecasts with the same forecast horizon we add the following equations to the model in (4) and (5):

$$E^{Liv}[\pi^2_{t+2}|\Omega_t] = E^M[\pi^2_{t+2}|\Omega_t] + \epsilon_{2,t} ;$$
$$E^{Liv}[\pi^4_{t+4}|\Omega_t] = E^M[\pi^4_{t+4}|\Omega_t] + \epsilon_{4,t} . \quad (7)$$

Equation (7) specifies that the Livingston survey forecasts differ from the Markov forecasts by a random error $\epsilon_{i,t}$, which allows for measurement error in the survey data.

Table 5 reports the results of LM tests for first-order serial correlation in the errors, $\epsilon_{i,t}$. These statistics are calculated from the sample likelihood for the whole model, equations (4) through (7), and thus take account of the sampling error in the Markov forecasts.[20] As the statistics show, these tests reveal little evidence of serial correlation. From this perspective, there is no evidence that the Livingston and Markov forecasts systematically diverge from one another.

Our second test compares the likelihood of future process switches implied by the survey forecasts with the transition probabilities estimates from the Markov model. In order to make the comparison, we will need to define the transition probabilities implicit in the survey data.

The Markov forecasts of future inflation depend upon the transition probabilities, q_1 and q_0, as indicated in equation (6). These probabilities are estimated from data

20. Since the Livingston Survey is available only twice a year and our inflation model is estimated on quarterly data, the equations in (7) can be formed only at every other observation. In these periods we assume that $\epsilon_{i,t}$ are normally distributed with mean zero and constant variances. Harvey (1990) describes how the likelihood function for the model specified in (4)–(7) can be formed under these circumstances. We maximize this likelihood and then perform the LM test. Table 5 reports the estimated covariance matrix of ($\epsilon_{2,t}$ $\epsilon_{4,t}$). The other parameter estimates are very similar to those reported in Table 4.

over the whole sample period.[21] These ex post estimates of the probabilities may well differ from the transition probabilities rational agents used to form their expectations at the time.

To see why the comparison of the two sets of probabilities is an important indicator of consistency between the survey forecasts and the Markov switching model, consider the behavior of inflation from the mid-1970s to the early 1980s. According to the Markov estimates, inflation followed a unit root process during this period so the estimated probability of remaining in this regime is high. That is, the ex post transition probabilities are heavily influenced by the realized behavior of inflation during this period. However, ex ante participants in the Livingston survey may have assigned a much smaller probability that inflation would switch to the unit root process at the start of the period than is warranted by the length of time a unit root process was followed ex post.

We can test whether the probabilities that summarize survey participants' perceptions about the likelihood of *future* process switches, which we call the *ex ante transition probabilities*, are equal to the *ex post transition probabilities* that govern realized switches in the inflation process over the sample. The test can be made by adding the following equations to the model in (4) and (5):

$$E^{Liv}[\pi^2_{t+2}|\Omega_t] = E^S[\pi^2_{t+2}|\Omega_t] + \epsilon_{2,t} \; ;$$

$$E^{Liv}[\pi^4_{t+4}|\Omega_t] = E^S[\pi^4_{t+4}|\Omega_t] + \epsilon_{4,t} \; . \tag{8}$$

where $E^{Liv}[.|.]$ are the Livingston survey forecasts as before and $E^S[.|.]$ represents a set of theoretical survey forecasts which allow the ex ante probabilities to differ from the ex post probabilities in (5). That is, $E^S[.|.]$ is defined as $E^M[.|.]$ in (6) except that the ex ante probabilities q_i^* replace the ex post probabilities q_i. We estimate the model given by (4), (5), and (8) with $q_0^* = q_0$ and $q_1^* = q_1$. Using these estimates we then conduct an LM test on the restrictions $q_0^* = q_0$ and $q_1^* = q_1$. As Table 5 shows, we cannot reject either restriction.

Our comparison of the Markov forecasts with the Livingston survey forecasts serves as an important validation of our model. In particular, our estimates of the transition probabilities that determine the degree of uncertainty about the inflation process[22] appear to closely match the probabilities implicitly contained in the survey forecasts. This means that estimates of inflation uncertainty derived from the Markov model will be consistent with the survey data.

Measures of Inflation Uncertainty

In section 2 we showed how uncertainty about switches in the inflation process affected both forecasts and the conditional variance of future inflation. We can now use the Markov model estimates to quantify these effects.

21. Engel and Hamilton (1990) point out that the estimates of the transition probabilities are closely related to the number of times during the sample that the process remained in a particular state between periods t and $t + 1$ measured as a fraction of the number of times it was in the state at t.

22. In the next section we will derive estimates of the conditional variance of inflation shown in equation (3) above.

Since the variance of inflation is related to the extent to which ex post bias is present in the forecast errors, we will begin with an analysis of the Markov model forecasts. Using our specification of the Markov switching model (4) and the definition of the k-period-ahead Markov forecast (6), we can write the forecast error as

$$\begin{aligned}\pi_{t+k} - E^M[\pi_{t+k}|\Omega_t] = {} & (\pi_{1,t+k} - E[\pi_{1,t+k}|\Omega_t])\, s_{t+k} \\ & + (\pi_{0,t+k} - E[\pi_{0,t+k}|\Omega_t])\,(1 - s_{t+k}) \\ & + (E[\pi_{1,t+k}|\Omega_t] - E[\pi_{0,t+k}|\Omega_t]) \\ & \times (s_{t+k}Pr(s_{t+k} = 0|\Omega_t) - (1 - s_{t+k})Pr(s_{t+k} = 1|\Omega_t))\,. \quad (9)\end{aligned}$$

The term on the first two lines on the right has a mean of zero and is uncorrelated with elements in the information set Ω_t. This term will, of course, be serially correlated when $k > 1$ because the k-period-ahead forecasts will overlap. The remaining term on the right identifies the ex post bias in the forecast error. It will generally not be equal to zero and depends on the size of the difference in the forecasts from the two states. More specifically, the ex post bias can be written as

$$\begin{aligned}& [\pi_{1,t} - \alpha_1^k\pi_{0,t} - \alpha_0(1 - \alpha_1^k)/(1 - \alpha_1)] \\ & \times [s_{t+k}Pr(s_{t+k} = 0|\Omega_t) - (1 - s_{t+k})Pr(s_{t+k} = 1|\Omega_t)]\,. \quad (10)\end{aligned}$$

Figure 4 plots the ex post bias for different forecast horizons calculated from our model estimates. The data are in percent per year and the bias is shown for forecast horizons of one, four, eight, and twelve quarters. As the figure shows, there is considerable ex post bias in the longer horizon forecasts during the 1970s and early 1980s. (Note that the vertical scale is different in each plot.) At the three-year horizon ($k = 12$) the bias ranges from 4 to -3 percent at annual rates. This indicates that long-term forecasts systematically under- and overpredicted actual inflation by quite substantial amounts as a direct consequence of uncertainty surrounding the inflation process.[23]

For example, if agents had been certain that inflation was going to continue to follow the random walk ($s_t = 1$) process once it had switched during the mid-1970s, $s_{t+k}Pr(s_{t+k} = 0|\Omega_t)$ would have been equal to zero, and the ex post bias would have been eliminated. Instead, uncertainty about the future inflation process meant that $Pr(s_{t+k} = 0|\Omega_t) > 0$, with the result that forecasts systematically underpredicted actual inflation (that is, there was positive ex post bias as the figure shows).[24]

Our Markov model estimates also allow us to examine the components of vari-

23. Note that the swings in the series do not reflect the effects of overlapping forecast errors since we are only plotting the ex post bias (10) and not the total forecast error (9).

24. The presence of ex post bias in inflation forecasts has a number of important consequences for empirical research. Evans and Lewis (1992), for example, argue that the presence of ex post bias has created a systematic divergence between ex ante and ex post real interest rates in the postwar period. Similarly, Evans and Wachtel (1992b) argue that much of the deflation in the early 1930s was unanticipated due to the presence of ex post bias.

ance of future inflation. The certainty equivalent and regime uncertainty components defined in (3) can be written more specifically in terms of the parameters of our model structure (4) as

$$\begin{aligned} E\{Var(\pi_{t+k}|\Omega_t, s_{t+k})|\Omega_t\} &= \Sigma_{i=0,1} Var(\pi_{i,t+k}|\Omega_t) Pr(s_{t+k} = i|\Omega_t) \\ &= k\sigma_1^2 Pr(s_{t+k} = 1|\Omega_t) \\ &\quad + [(1 - \alpha_1^{2k})/(1 - \alpha_1)]\sigma_0^2 Pr(s_{t+k} = 0|\Omega_t) \quad (11a) \end{aligned}$$

and

$$\begin{aligned} Var\{E(\pi_{t+k}|\Omega_t, s_{t+k})|\Omega_t\} &= [E(\pi_{1,t+k}|\Omega_t) - E(\pi_{0,t+k}|\Omega_t)]^2 \\ &\quad \times Pr(s_{t+k} = 1|\Omega_t) Pr(s_{t+k} = 0|\Omega_t) \\ &= \{\pi_{1,t} - [\alpha_1^k \pi_{0,t} + \alpha_0(1 - \alpha_1^k)/(1 - \alpha_1)]\}^2 \\ &\quad \times Pr(s_{t+k} = 1|\Omega_t) Pr(s_{t+k} = 0|\Omega_t) \,. \quad (11b) \end{aligned}$$

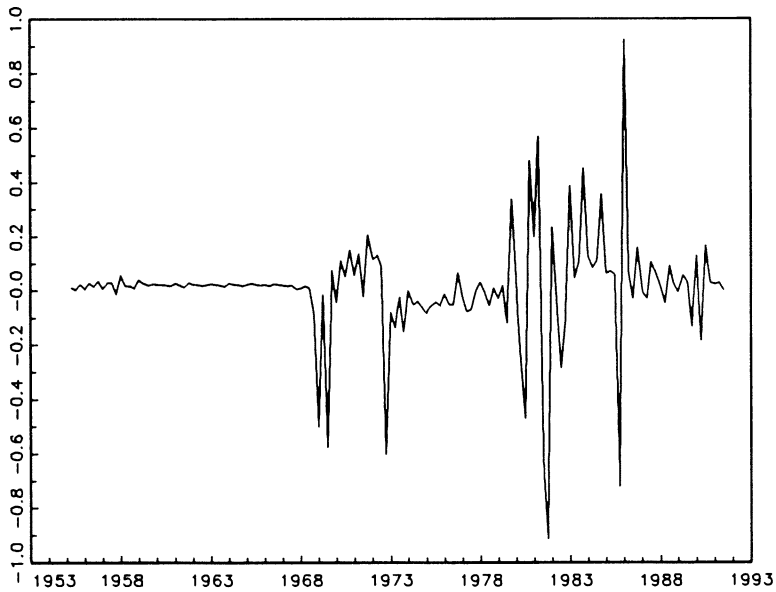
Comparing (11b) with (10) we see that the regime uncertainty component is equal to the expectation of the squared ex post bias in the k-period-ahead inflation forecasts.

Figure 5 plots various measures of inflation uncertainty calculated from the maximum likelihood estimates of the Markov model. Because the variance components have an enormous range, we show the square root of the total variance of inflation, $\sqrt{Var(\pi_{t+k}|\Omega_t)}$, and the square root of the regime uncertainty component, $\sqrt{Var(E[\pi_{t+k}|\Omega_t, s_{t+k}]|\Omega_t)}$. The uncertainty measures are shown for forecast horizons of one, four, eight, and twelve quarters.

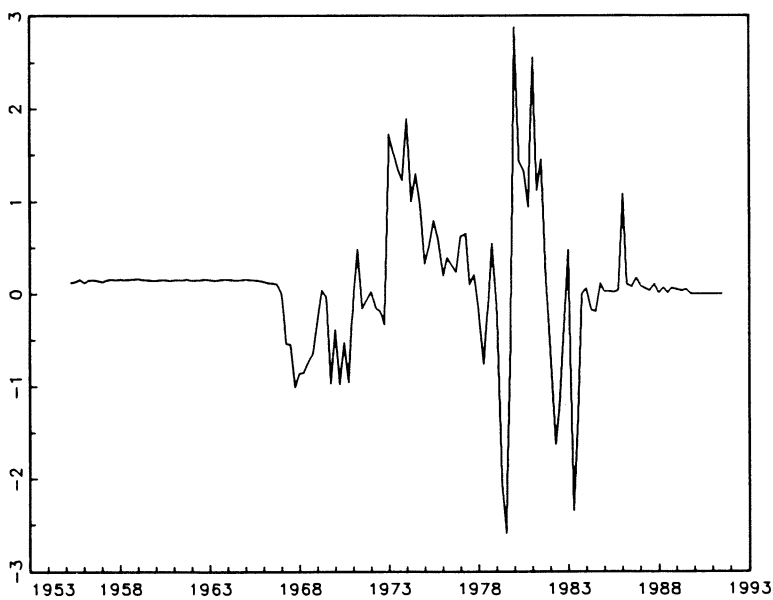
Generally, the figure shows that inflation uncertainty increases at all horizons in 1968 and does not return to the low levels of the 1950s and 1960s until 1984. Uncertainty about the inflation process, regime uncertainty, varies more than the total. The standard deviation of regime uncertainty component rises to approximately half the standard deviation of total uncertainty around 1973 and 1979, after the oil price shocks. As one might expect, regime uncertainty appears to have contributed most to total uncertainty during periods where the swings in inflation have been largest. The figure also shows that the regime uncertainty component is greater at longer forecast horizons. At the two-quarter horizon the component peaks at over 3 percent, compared to 1.2 percent at one quarter. It thus appears that regime uncertainty is more important when considering long- rather than short-term inflation uncertainty.

Figure 5 also shows that at longer horizons ($k > 1$) variations in the regime uncertainty component closely follow the swings in the rate of inflation (shown in Figure 2). Ball and Cecchetti (1990) and Evans (1991) find similar positive correlations between the level of inflation and estimates of long-term inflation uncertainty.

There have been other studies that have examined the relationship between inflation uncertainty and the level of inflation; see, for example, Wachtel (1977), Cukierman and Wachtel (1979), and Holland (1984) which includes a summary of prior

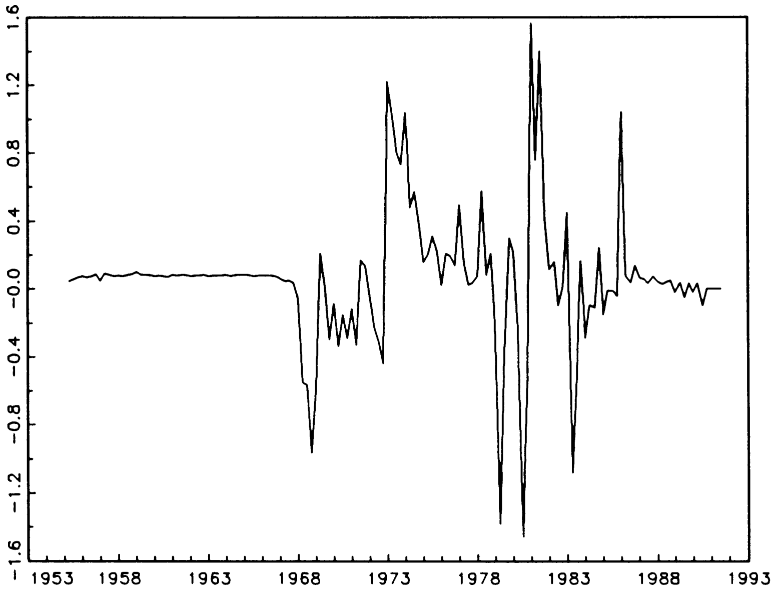


k = 1

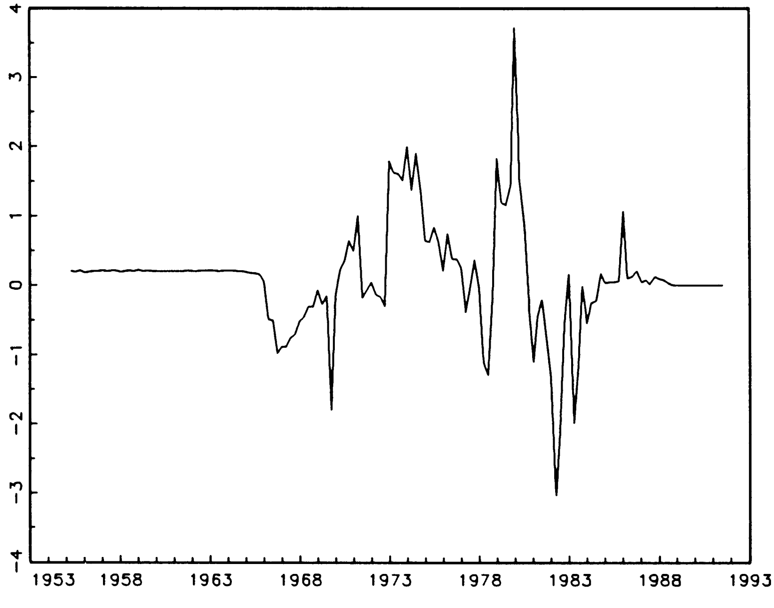


k = 8

FIG. 4. (this page and next) Estimates of Ex Post Bias in Inflation Forecasts, $\pi_{t+k} - E[\pi_{t+k}|\Omega_t]$, in percent per annum. Notes: Estimates are calculated from $[\pi_{1,t} - \alpha_1^k\pi_{0,t} - \alpha_0(1 - \alpha_1^k)/(1 - \alpha_0)][s_{t+k}Pr(s_{t+k} = 0|\Omega_t) - (1 - s_{t+k})Pr(s_{t+k} = 1|\Omega_t)]$ using the parameter estimates reported in Table 4.


1.6
1.2
0.8
0.4
-0.0
-0.4
-0.8
-1.2
-1.6
1953
1958
1963
1968
1973
1978
1983
1988
1993

k = 4


4
3
2
1
0
-1
-2
-3
-4
1953
1958
1963
1968
1973
1978
1983
1988
1993

k = 12

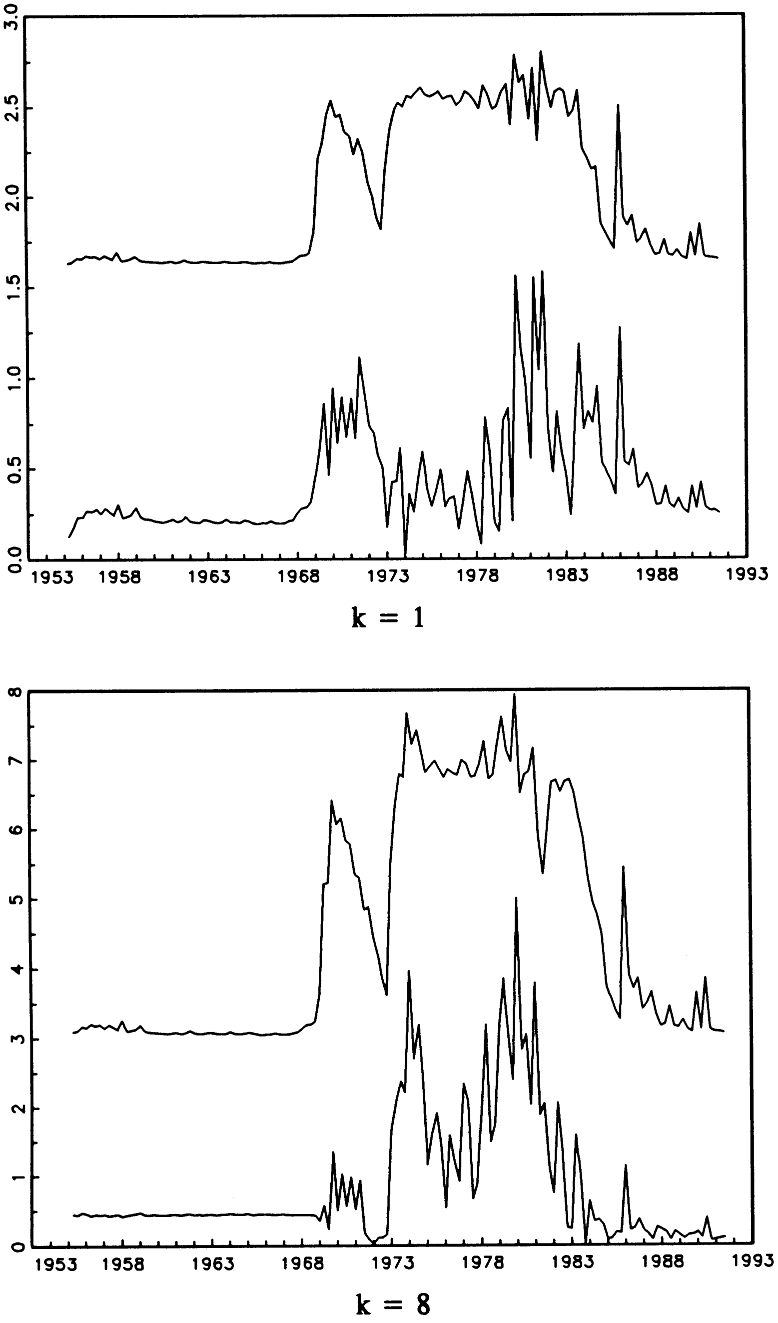
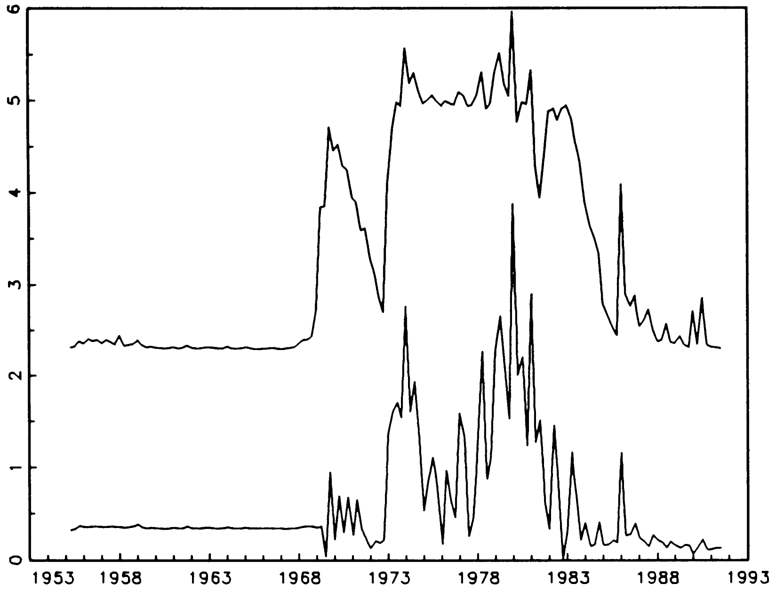
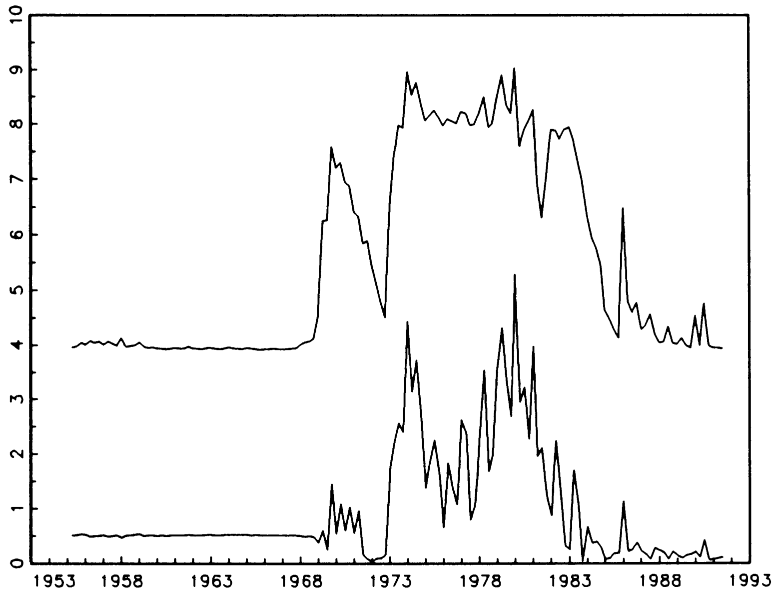


FIG. 5. Estimated Components of Inflation Uncertainty at Different Horizons (k months). Notes: The top line in each plot is the conditional standard deviation of quarterly inflation k months ahead, $\sqrt{\mathrm{VAR}(\pi_{t+k}|\Omega_t)}$. The lower line plots the square root of the regime uncertainty component k months ahead, $\sqrt{\mathrm{Var}\{E(\pi_{t+k}|\Omega_t, s_{t+k})|\Omega_t\}}$. Both series are expressed in percent per annum.



6
5
4
3
2
1
0
1953
1958
1963
1968
1973
1978
1983
1988
1993

k = 4



10
9
8
7
6
5
4
3
2
1
0
1953
1958
1963
1968
1973
1978
1983
1988
1993

k = 12

studies. However, these studies tended to use crude proxies for uncertainty, such as a moving variance of the inflation rate or the cross-sectional variance of survey respondents. These measures are difficult to interpret and do not directly correspond to either component of the conditional variance. In fact, the commonly used survey measures of the variance of expectations may have little to do with any aspect of inflation uncertainty. Cross-sectional variation in respondent forecasts could simply reflect difference in the information sets used to forecast.[25] Alternatively, the survey variance may reflect differences in the way respondents use a common information set to forecast. One might expect these differences to be greatest when there is most uncertainty about the current and future inflation process. In this case the survey measures may proxy for the regime uncertainty component of the conditional variance of inflation.

To investigate these alternatives, we compared the cross-sectional standard deviations of respondents' forecasts from the three surveys against the estimates of inflation uncertainty derived from our Markov model. The closest relationship was found between the survey measure of dispersion and the regime uncertainty component. Figure 6 shows that these series have moved closely with one another during the past fifteen years.[26] This suggests that regime uncertainty has been an important source of the cross-sectional variation in the respondent forecasts which have been frequently used as survey measures of inflation uncertainty.[27]

To summarize, our Markov model estimates suggest that uncertainty about the inflation process significantly contributes to the overall degree of inflation uncertainty as measured by the conditional variance of future inflation. Uncertainty about the inflation process also appears to create a sizable ex post bias in long-term inflation forecasts. This bias matches the systematic difference between Livingston survey forecasts and actual inflation suggesting that the survey respondents rationally account for regime uncertainty when forecasting. This finding contradicts the view that the survey forecasts of inflation are "irrational." We have also shown that variations in the survey measures of inflation uncertainty closely match the movements in the regime uncertainty component of inflation's conditional variance. This suggests that uncertainty about the inflation process accounts for at least some of the dispersion in survey forecasts.

4. ECONOMIC ACTIVITY AND INFLATION UNCERTAINTY

In this section we use our measures of inflation uncertainty to explore the link between inflation uncertainty and economic activity. In particular, we shall focus on

25. Fishe and Idson (1990) provide some support for the use of differential information in their examination of the SRC data. They find that the variation across individual respondents is related to factors that determine the respondents' demand for information.

26. For ease of comparison, Figure 6 plots the deviations of each series about their sample means divided by their sample standard deviation.

27. Interestingly, if the survey measures of uncertainty proxy for the regime uncertainty component, as Figure 6 indicates, and this component is positively correlated with the level of inflation, as Figure 5 shows, our findings predict a positive correlation between the survey measures of uncertainty and inflation. This accords with findings in the literature; see, for example, Cukierman and Wachtel (1979).

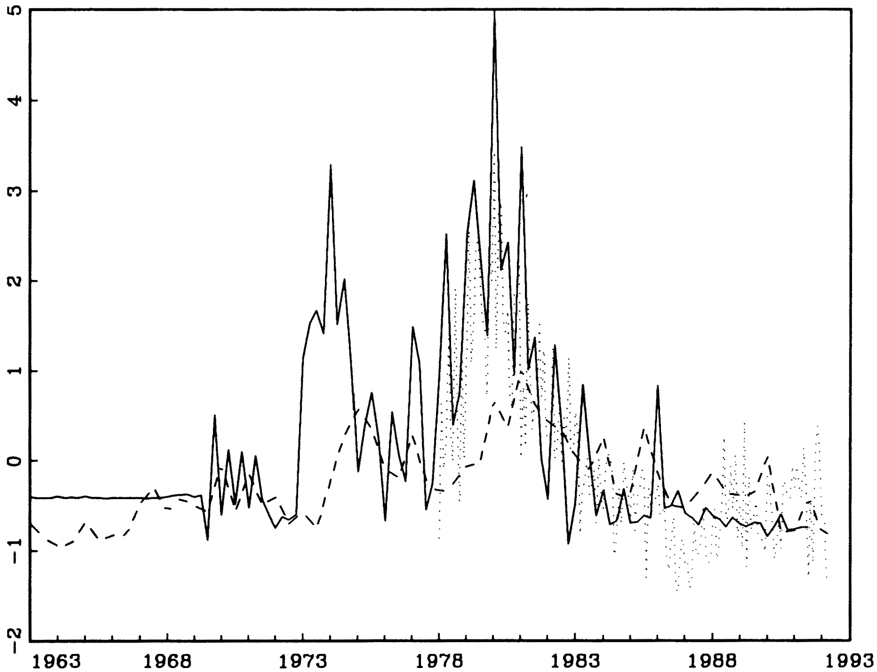


FIG. 6. Alternative Measures of Inflation Uncertainty. Notes: The plotted series are: ——— the square root of the regime uncertainty component four months ahead, $\sqrt{\mathrm{Var}\{E(\pi_{t+k}|\Omega_t s_{t+4})|\Omega_t\}}$, — — — the standard deviation of six-month Livingston forecasts, and .... the standard deviation of the twelve-month SRC forecasts. All series are standardized by subtracting the sample means and dividing the result by its sample standard deviation.

the relationship between unemployment and inflation uncertainty using vector autoregressions (VARs).

There is an extensive theoretical literature that attempts to show why uncertainty should affect behavior and an equally extensive empirical literature that attempts to document the relationship. In particular, both Okun (1971) and Friedman (1977) noted the importance of inflation uncertainty and suggested that it might worsen the trade-off between inflation and unemployment. The empirical relationship between inflation uncertainty and real activity has been explored by Wachtel (1977), Amihud (1981), Mullineaux (1980), Levi and Makin (1980), and more recently by Jansen (1989), and Holland (1993). The existing empirical literature makes use of various measures of inflation uncertainty including the variability of inflation itself, the dispersion of inflation forecasts from the Livingston or other surveys, and estimates of the variance of inflation from time series modeling of the inflation process. Generally, the results of these studies have been mixed. There is some evidence of a negative uncertainty effect on real activity, but it is usually sensitive to the choice of sample period and it is rarely robust to changes in specification. In sum, there is little consensus about whether inflation uncertainty affects real economic activity, or what aspect of uncertainty has the most influence on behavior.

Our Markov model, which can be viewed as a nonlinear time series process for inflation, provides a new measure of inflation uncertainty. Moreover, the measure of inflation uncertainty derived from our model allows us to interpret two important aspects of uncertainty that might affect real activity. First, as described above, we will distinguish between the certainty equivalent and regime uncertainty components of the conditional variance of inflation. Since the existence of regime shifts in our model has enabled us to explain the behavior of inflation and inflation forecasts quite well, we expect that uncertainty due to the possibility of regime shifts will be important.

Second, we will examine the effects of inflation uncertainty over forecast horizons of different lengths. We suspect that intertemporal decision making—including the negotiation of long-term employment contracts—is more likely to be affected by variations in long-term rather than short-term inflation uncertainty. Consequently, the sole use of a short-term measure to determine whether inflation uncertainty affects unemployment may produce unreliable results when the short-term prospects for inflation differ significantly from the long-term prospects. Such differences were discussed in Klein (1977) and documented in Ball and Cecchetti (1990) and Evans (1991). They are also apparent in Figure 4.

We examine the effects of inflation uncertainty using the well-known VAR methodology. The results presented below are derived from VARs that included the unemployment rate, the first difference of the quarterly (CPI) inflation rate, the spread between the ten-year government bond rate and the Federal Funds rate, and various measures of inflation uncertainty. We include the first difference of inflation to account for the presence of the unit root in the inflation rate itself (see Table 1). The interest rate spread variable is used as indicator of the influence of monetary policy.[28] The VARs were estimated with data for 1965 to 1991 and include six lags of each variable and a constant term.

To begin, we estimated VAR systems with both the certainty equivalence and regime uncertainty components, $V_{CE}(k) \equiv E\{Var(\pi_{t+k}|\Omega_t, s_{t+k})|\Omega_t\}$ and $V_{RU}(k) \equiv Var\{E(\pi_{t+k}|\Omega_t, s_{t+k})|\Omega_t\}$, of the variance of inflation. Each VAR system includes the two components of inflation uncertainty at a different forecast horizon, that is, $k =$ one, four, eight, or twelve quarters. That is, each VAR included the unemployment rate, the difference in the inflation rate, the interest rate spread, and two measures of inflation uncertainty, $V_{CE}(k)$ and $V_{RU}(k)$. The results indicate that the inflation uncertainty components are not Granger caused by any of the other variables. There are weak causal links in both directions between unemployment and the change in the inflation rate. There is significant causality in both directions between the interest rate spread and the unemployment rate. Our primary interest, however, is the effect of inflation uncertainty on real economic activity, the unemployment rate.

Table 6 shows the influence of the two variance components in the unemployment equation from the VAR systems that use the inflation variances at different forecast

28. See Friedman and Kuttner (1992) for a discussion of interest rate spreads as indicators of monetary policy. It is useful in our data period because it avoids the difficulties introduced by (i) structural changes that alter the meaning of money and credit aggregates and (ii) changes in the intermediate target for policy.

TABLE 6

VECTOR AUTOREGRESSION RESULTS 1965.I–1991.I

	Marginal Significance Level of Uncertainty Measures in Forecasting Unemployment	
Horizon (k)	Certainty Equivalence Variance, $V_{CE}(k)$	Regime Uncertainty Variance, $V_{RU}(k)$
1	0.487 (0.669)	0.100 (0.137)
4	0.894 (0.946)	0.100 (0.090)
8	0.858 (0.935)	0.045 (0.035)
12	0.821 (0.928)	0.022 (0.025)

NOTES: The VAR systems include the unemployment rate, the first difference of the inflation rate, the spread between the ten-year government bond rate and the Federal Funds rate, $V_{CE}(k)$ and $V_{RU}(k)$. The statistics shown are explained in the text.

horizons ($k = 1,4,8,12$). Each row reports the marginal significance levels for the influence of the two variance uncertainty components on the unemployment rate from a VAR with the inflation variances at forecast horizon k. The upper entry is the marginal significance derived from the standard F-test that ignores the fact that the two variance measures, $V_{CE}(k)$ and $V_{RU}(k)$, are estimates that contain sampling errors. To assess the importance of this problem we ran some Monte Carlo experiments to calculate the marginal significance levels under the extreme assumption that estimated components were completely dominated by sampling error.[29] These statistics are reported in parentheses.

The results in Table 6 are quite striking. The marginal significance tests indicate that the certainty equivalence component $V_{CE}(k)$, does not contribute significantly to the predictable variation in the unemployment rate while the regime uncertainty component, $V_{RU}(k)$, makes a dramatic contribution. At longer forecasting horizons, k, the lags of $V_{RU}(k)$ are significant at the 5 percent level. That is, uncertainty about the inflation regime that will prevail in two or three years has a significant influence on real economic activity. These findings appear robust to the presence of sampling variation in $V_{CE}(k)$ and $V_{RU}(k)$. The significance levels in parenthesis show that the F-statistics on lagged $V_{CE}(k)$ are quite likely to be observed if the component were completely dominated by sampling noise. By contrast, there is less than a 5 percent probability of observing our calculated F-statistics on $V_{RU}(k)$, if in fact these components were dominated by sampling noise.

The results so far indicate that the certainty equivalent component of inflation uncertainty, $V_{CE}(k)$, does not have any influence on real activity. To explore the in-

29. The Monte Carlo experiments were carried out as follows: First, for each k, we generated independent series for $V_{CE}(k)$ and $V_{RU}(k)$ that matched the variance and first-order autocorrelations of the estimated components. Next, we ran the VAR using actual data for unemployment, inflation, and the spread, and the generated data for the components. From the estimates we calculated the F-statistics for the hypotheses that unemployment is exogenous with respect to the generated components. This procedure was repeated one thousand times to generate an empirical distribution for the F-statistics. To calculate the marginal significance levels reported in the table we compared the F-statistics based on our estimates of V_{CE} and V_{RU} against the empirical distributions.

TABLE 7

VECTOR AUTOREGRESSION RESULTS 1965.I–1991.I

Panel I:

	Variance Decompositions of Unemployment h Quarters Ahead			
	h = 1	h = 4	h = 8	h = 12
Forecast Horizon (k)				
$V_{RU}(1)$	0.006 (0.956)	1.891 (0.802)	1.452 (0.801)	0.715 (0.947)
$V_{RU}(4)$	2.636 (0.145)	4.243 (0.235)	10.812 (0.094)	26.406 (0.006)
$V_{RU}(8)$	3.759 (0.083)	6.553 (0.106)	15.243 (0.022)	27.794 (0.004)
$V_{RU}(12)$	3.829 (0.065)	7.438 (0.087)	16.657 (0.020)	27.231 (0.009)

Panel II:

	Variance Decompositions of Unemployment h Quarters Ahead with $V_{RU}(12)$			
	h = 1	h = 4	h = 8	h = 12
Variable				
Unemployment	89.022 (1.000)	71.103 (0.885)	43.156 (0.777)	24.823 (0.545)
Inflation	6.440 (0.348)	20.216 (0.557)	12.834 (0.659)	8.027 (0.923)
Spread	0.709 (1.000)	3.112 (0.321)	27.354 (0.975)	39.919 (0.989)
$V_{RU}(12)$	3.829 (0.065)	7.438 (0.087)	16.657 (0.020)	27.231 (0.009)

NOTES: The VAR systems include the unemployment rate, the first difference of the inflation rate, the spread between the ten-year government bond rate and the Federal Funds rate, and $V_{RU}(k)$. The statistics shown are explained in the text.

fluence of regime uncertainty further, we estimated four variable VAR systems—with unemployment, the first difference of inflation, the interest rate spread, and $V_{RU}(k)$ for k = 1,4, 8, or 12.[30]. Variance decompositions for each of these systems were calculated with the variables ordered as above and some selected results are shown in Table 7.

Panel I of Table 7 shows the influence of regime uncertainty at different forecast horizons, k, on the variance of unemployment h quarters ahead. Thus, each row in this panel includes results from a different VAR. In Panel II of Table 7, we show the influence of all the variables in the system on the variance of unemployment forecasts h quarters ahead. This panel includes results from the VAR system that includes $V_{RU}(12)$. The upper entries in the table are the percentage of the variance in unemployment (in Panel I) or the variable indicated (in Panel II) at an h-quarter forecast horizon that is attributable to variations in $V_{RU}(k)$. In parentheses are the marginal significance levels calculated from Monte Carlo simulation for the hypoth-

30. The results of Granger-causality tests for these systems are no different from those discussed above for the five-variable VAR systems.

esis that $V_{RU}(k)$ is an independent process.[31] They can be interpreted as the probability of observing the variance percentage shown when the estimates of $V_{RU}(k)$ are dominated by random sampling noise.

The results in Panel I indicate that the regime uncertainty component of the variance of inflation forecasts makes an important contribution to unemployment forecasts, particularly when regime uncertainty is calculated with a forecast horizon of eight or twelve quarters. The conclusion that regime uncertainty influences the variance of unemployment holds for the variance measure derived from any forecast horizon except one quarter. For such short forecast horizons, there is simply not very much uncertainty about potential regime switches. However, regime changes are an important source of uncertainty for inflation forecasts with horizons of four quarters or more. Consequently, $V_{RU}(k)$ has an increasing influence on unemployment forecasts as the forecast horizon (h) increases. As much as 27 percent of the variation in twelve-quarter-ahead unemployment forecasts is due to the regime uncertainty in longer-horizon inflation forecasts. In addition, the influence of longer-horizon regime uncertainty on longer-term unemployment forecasts is highly significant.

A more complete picture of the role of inflation uncertainty in explaining the variation in unemployment forecasts is presented in Panel II. Here we show the complete variance decomposition for the unemployment rate from the four-variable VAR system with $V_{RU}(12)$. That is, the panel reproduces the results in the last row of Panel I and also shows the influence of the other variables in the system on the unemployment forecasts with various horizons.

The change in the inflation rate has the strongest effect on the variance of the unemployment forecasts at relatively shorter horizons. As the forecast horizon lengthens, the influence of the interest rate spread (our monetary policy proxy) and V_{RU} increase. At a twelve-quarter-forecast horizon V_{RU} has a stronger explanatory role than the past history of unemployment itself, although it is not as important as the interest rate spread.

All of the VAR models discussed were also estimated with different specifications and different lag lengths to check the robustness of our results. Specifically, we estimated the models with an alternative interest rate spread (the difference between the AAA corporate bond yield and the Federal Funds rate) and with the spread variable excluded altogether. We also estimated the VARs with lag lengths varying between four and eight quarters. The results shown in Table 6 are robust to all these variations in the specification of the VAR system.

Overall, our findings suggest that uncertainty about the future inflation process (measured by the regime uncertainty component) rather than future inflation shocks (measured by the certainty equivalent component) significantly affects unemployment even after we account for the effects of inflation and monetary policy (as indi-

31. Specifically, we generated series for $V_{RU}(k)$ in the same way as our earlier experiments. Then, we estimated a VAR using actual data for unemployment, inflation, and the spread, and the generated $V_{RU}(k)$ data. This procedure was repeated one thousand times to generate an empirical distribution for the variance decompositions. The marginal significance levels are then calculated by comparing the upper entries in the table to these empirical distributions.

cated by the spread). As we note above, variations in the regime uncertainty component are closely linked to the presence of ex post bias in rational inflation forecasts. Thus, our results also suggest that inflation uncertainty is costly in part because it leads to ex post bias in inflation forecasts. From this perspective, it is not surprising to find that the regime uncertainty component has the larger effect on unemployment as the horizon lengthens because the bias in rational forecasts tends to grow with the forecast horizon.

Our findings also appear to reconcile the results of past research on the effects of inflation uncertainty. Since the survey measures of uncertainty seem to proxy for the regime uncertainty component, our results appear consistent with Cukierman and Wachtel (1979) among others who find that the survey measures affect behavior. By contrast, studies using ARCH estimates have failed to find significant effects; see Jansen (1989). Since simple ARCH measures of uncertainty do not contain any regime uncertainty components, these results also appear consistent with our findings.

To summarize, the results in this section confirm that *some* aspects of inflation uncertainty affect behavior. Uncertainty surrounding the future inflation regime at horizons of two to three years, in particular, appears to have significantly affected unemployment. Short-term uncertainty, whatever its source, seems to have much less effect.

CONCLUSIONS

The results in this paper highlight the importance of changes in inflation regime. Our model demonstrates that there have been distinct switches in the inflation regime during the past thirty-five years. The estimates showed that these switches would have sizable effects upon rational agents' forecasts and the degree of uncertainty associated with future inflation. Importantly, we also showed that the Livingston survey forecasts exhibit the same degree of ex post bias as rational forecasts that account for the effects of process switches. Since ex post bias is observed in other survey forecasts, this finding undermines the idea that these forecasts are in some sense "irrational."

Using our model estimates we decomposed uncertainty about future inflation into two components: a certainty equivalent component and a regime uncertainty component. This decomposition allowed us to investigate whether any particular aspect of inflation uncertainty affected behavior more than others. We found that uncertainty surrounding the future inflation regime at horizons of two to three years significantly affected unemployment. Short-term uncertainty, by contrast, had much less effect.

Overall, these findings suggest that much more attention needs to be paid to the consequences of regime switching when estimates of expected inflation or inflation uncertainty are used in applied research. Uncertainty about the inflation process leads rational agents to make forecasts that appear systematically biased when viewed with hindsight. Ignoring this can lead to false inferences about the behavior of expected real returns, as Evans and Lewis (1992) argue. Similarly, as our results indicate, estimates of inflation uncertainty that ignore the effects of regime switches may seriously underestimate both the degree of uncertainty and its consequences.

Finally, it is worth pointing to an important issue which we have not addressed. Our switching model does not relate switches in the inflation process to changes in either private sector behavior and/or government policy. This is undoubtedly a challenging yet worthwhile task. For if changes in monetary policy have been responsible for some of the switches in regimes, our findings suggest that there would be significant benefits from either institutional or procedural measures that reduced the degree of uncertainty about future policy.

LITERATURE CITED

Amihud, Yakov. "Price Level Uncertainty, Indexation and Employment." *Southern Economic Journal* 47 (January 1981) 776–87.

Ball, Laurence, and Stephen Cecchetti. "Inflation Uncertainty at Short and Long Horizons." *Brookings Papers on Economic Activity* (1990:1) 215–54.

Brown, R. L., J. Durbin, and J. M. Evans. "Techniques for Testing the Constancy of Regression Relationships over Time." *Journal of the Royal Statistical Society Series B* 37 (1975), 149–63.

Carlson, John. "A Study of Price Forecasts." *Annals of Economic and Social Measurement* 6 (Winter 1977), 27–56.

Cosimano, Thomas, and Dennis Jansen. "Estimates of the Variance of U.S. Inflation Based upon the ARCH Model: Comment." *Journal of Money, Credit, and Banking* 20 (August 1988, Part 1), 409–21.

Cukierman, Alex, and Paul Wachtel. "Differential Inflationary Expectations and the Variability of the Rate of Inflation: Theory and Evidence." *American Economic Review* (September 1979), 595–609.

Cumby, Robert E., and John Huizinga. "Testing the Autocorrelation Structure of Disturbances in Ordinary Least Squares and Instrumental Variables Regressions." *Econometrica* 60 (January 1992), 185–98.

Engle, Robert. "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica* 50 (1982), 987–1007.

______. "Estimates of the Variance of U.S. Inflation Based upon the ARCH Model." *Journal of Money, Credit, and Banking* 15 (August 1983), 286–301.

Evans, Martin. "Discovering the Link between Inflation Rates and Inflation Uncertainty." *Journal of Money, Credit, and Banking* 23 (May 1991), 169–84.

Evans, Martin, and Karen Lewis. "Do Expected Shifts in Inflation Policy Affect Real Rates." National Bureau of Economic Research working paper No. 4134, 1992.

Evans, Martin, and Paul Wachtel. "Interpreting the Movements in Short-Term Interest Rates." *Journal of Business* 65 (July 1992), 395–429. a

______. "Were Price Changes during the Great Depression Anticipated? Evidence from Nominal Interest Rates." (September 1992). b

Figlewski, Stephen, and Paul Wachtel. "The Formation of Inflationary Expectations." *The Review of Economics and Statistics* 53 (February 1981), 1–10.

Fishe, Raymond P. H., and Todd Idson. "Information-Induced Heteroscedasticity in Price Expectations Data." *The Review of Economics and Statistics* 72 (May 1990), 304–12.

Friedman, Benjamin, and Kenneth Kuttner. "Money, Income, Prices, and Interest Rates." *American Economic Review* 82 (June 1992), 472–92.

Friedman, Milton. "Nobel Lecture: Inflation and Unemployment." *Journal of Political Economy* 85 (June 1977), 451–72.

Hamilton, James D. "Analysis of Time Series Subject to Changes in Regime." *Journal of Econometrics* 45 (1990), 39–70.

Hansen, Bruce E. "Testing for Parameter Instability in Linear Models." University of Rochester working paper, May 1991.

Harvey, Andrew C. *Forecasting Structural Time Series Models and the Kalman Filter.* Cambridge University Press, 1990.

Holland, A. Steven. "Does Higher Inflation Lead More Uncertain Inflation?" Federal Reserve Bank of St. Louis *Review* 66 (February 1984), 15–26.

______. "Uncertain Effects of Money and the Link between the Inflation Rate and Inflation Uncertainty." *Economic Inquiry* 31 (January 1993), 39–51.

Jaffee, Dwight, and Ephraim Kleiman. "The Welfare Implications of Uneven Inflation." In *Inflation Theory and Anti-Inflation Policy*, edited by Erik Lundberg. Boulder, Colo.: Westview Press, 1977.

Jansen, Dennis. "Does Inflation Uncertainty Affect Output Growth? Further Evidence." Federal Reserve Bank of St. Louis, *Review* (July/August 1989), 43–54.

Klein, Benjamin. "Our New Monetary Standard: The Measurement and Effects of Price Uncertainty, 1880–1973." *Economic Inquiry* 13 (December 1975), 461–84.

______. "The Social Costs of Recent Inflation: The Mirage of Steady Anticipated Inflation." In *Institutional Arrangements and the Inflation Problem*, edited by K. Brunner and A. Meltzer. North Holland: Carnegie-Rochester Conference Series on Public Policy, Vol. 3, 1977.

Levi, Maurice, and John Makin. "Inflation Uncertainty and the Phillips Curve: Some Empirical Evidence." *American Economic Review* 70 (December 1980), 1022–27.

Lewis, Karen K. "Changing Beliefs and Systematic Forecast Errors." *American Economic Review* 79 (September 1989), 621–36.

______. "Was There a 'Peso Problem' in the U.S. Term Structure of Interest Rates: 1979–1982?" *International Economic Review* 32 (1991), 159–73.

Logue, Dennis, and Thomas Willett. "A Note on the Relation between the Rate and Variability of Inflation." *Economica* 43 (May 1976), 151–58.

Mullineaux, Donald. "Unemployment, Industrial Production, and Inflation Uncertainty in the United States." *The Review of Economics and Statistics* (May 1980), 163–69.

Okun, Arthur. "The Mirage of Steady State Inflation." *Brookings Papers on Economic Activity* (2:1971), 485–98.

Perron, Pierre. "The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis." *Econometrica* 57 (1989), 1361–1401.

Pesando, James. "A Note on the Rationality of the Livingston Price Expectations." *Journal of Political Economy* 83 (1975), 849–58.

Rogoff, Kenneth S. "Essays on Expectations and Exchange Rate Volatility." Ph.D. Dissertation, Massachusetts Institute of Technology, 1980.

Taylor, John B. "On the Relation between the Variability of Inflation and Average Inflation Rates." Carnegie-Rochester Conference Series on Public Policy, pp. 57–85, 1981.

Wachtel, Paul. "Survey Measures of Expected Inflation and Their Potential Usefulness." In *Analysis of Inflation: 1965–74*, edited by Joel Popkin. National Bureau of Economic Research, 1977.

Zarnowitz, Victor. "Rational Expectations and Macroeconomic Forecasts." *Journal of Business and Economic Statistics* 3 (October 1985), 289–311.

Zivot, Eric, and Donald W. K. Andrews. "Further Evidence on the Great Crash, the Oil Price Shock, and the Unit Root Hypothesis." *Journal of Business and Economic Statistics* 10 (July 1992), 251–270.