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Forecasts of Inflation From Var Models

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FORECASTS OF INFLATION FROM VAR MODELS

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FORECASTS OF INFLATION FROM VAR MODELS

ABSTRACT

Why are forecasts of inflation from VAR models so much worse than their forecasts of real variables? This paper documents that relatively poor performance, and finds that the price equation of a VAR model fitted to U.S. postwar data is poorly specified. Statistical work by other authors has found that coefficients in such price equations may not be constant. Based on specific monetary actions, two changes in monetary policy regimes are proposed. Accounting for those two shifts yields significantly more accurate forecasts and lessens the evidence of misspecification.

Key words: Inflation forecasts, vector autoregressive models, monetary policy regimes.

FORECASTS OF INFLATION FROM VAR MODELS

Forecasts of real macroeconomic statistics for the United States have been successfully produced by vector autoregressive (VAR) models. McNees (1986), for example, compared a series of published forecasts produced in the early 1980s by Robert Litterman's VAR model with forecasts made by conventional macroeconomic forecasters. McNees's comparisons showed Litterman's forecasts to be more accurate than six competitors for real GNP growth and the unemployment rate for forecasts varying in length from one to eight quarters ahead. In addition, Webb (1991) compared simulated forecasts of business cycle turning points generated by a VAR model adjusted by individually set lag lengths (AVAR) with actual forecasts from three large forecasting services. That study found little difference for one-quarter-ahead forecasts but superior performance by the AVAR for four-quarter-ahead forecasts.

VAR forecasts of inflation have been less successful relative to other forecasts. McNees's data shows that the average error of the series of Litterman's inflation forecasts was typically the worst of several that were compared, with his errors often double those of the best forecaster. Zarnowitz and Braun (1991) also simulated VAR forecasts from a model with restrictions similar to Litterman's, which is often referred to as a BVAR model. In comparison with actual forecasts included in the National Bureau of Economic Research-American Statistical Association survey, they found "The BVAR forecasts of [real GNP] perform relatively well .... but the BVAR forecasts of ... [the GNP implicit price deflator] are apparently much weaker." Simulated forecasts of inflation from models that are presented below are often less accurate than simply predicting no change.

This paper attempts to diagnose the source of inaccurate inflation forecasts and to suggest a direction for improvement. The relatively poor performance of several models is first documented. In the next section evidence of misspecification is presented for representative price equations from two models. Possible sources of misspecification are next examined;

evidence is presented that the price equations' coefficients are unstable due to two monetary policy regime changes. A possible remedy is evaluated by means of simulated forecasts.

RELATIVELY POOR PERFORMANCE OF VAR INFLATION FORECASTS

VAR MODELS

A VAR model uses historical data to predict future values. An unrestricted VAR (UVAR) model can be written

$$\boldsymbol{X} = \mu + \beta(L)\boldsymbol{X} + \varepsilon \tag{1}$$

where $\boldsymbol{X}$ is a $k\times1$ vector of variables, μ is a $k\times1$ vector of constant terms, $\beta(L)$ is a polynomial of degree m in the lag operator (L), and ε is a $k\times1$ vector of error terms. In practice, a k-variable model is often simply k separate equations for which the coefficients can be estimated by ordinary least squares. The price equation in the UVAR considered below is

$$p_t = \mu_p + \sum_{v=1}^{k}\sum_{j=1}^{m} \beta_{j,v}X_{v,t-j} + \varepsilon_t \tag{2}$$

where p is the inflation rate, t indexes time, v indexes the particular variable, j indexes the lag number, and μ_p and the $\beta_{j,v}s$ are coefficients.

Note that even for a relatively small VAR model such as the one used in this paper, with the number of variables k=5 and the lag length m=6, the price equation contains 31 coefficients to be estimated. It is often believed desirable to limit the number of estimated coefficients. As Doan put it, "Forecasts made using unrestricted vector autoregressions often suffer from the overparameterization of the models ... [which] causes large out-of-sample forecast errors."[1] In addition, Hafer and Sheehan (1989) presented evidence that led them to conclude that "relatively short-lagged [VAR] models [tend] to be more accurate, on average, than longer-lagged specifications." More typically, Engle and Yoo (1987) have simply asserted that "The forecasting performance of unrestricted VARs has not been particularly good ...."

In order to limit the number of estimated parameters, this paper's strategy is to reduce many lag lengths in an adjusted VAR (AVAR) model. For each equation, set two lag lengths -- one for the dependent variable and another for all independent variables -- in order to optimize some statistical criterion. The particular criterion used in this paper is the Schwarz Criterion (SC), which typically gives a parsimonious specification.[2] It is defined as

$$SC = T \ln \hat{\sigma}^2 + N \ln T \tag{3}$$

where T is the number of observations, N is the number of estimated coefficients, and $\hat{\sigma}^2$ is the estimated residual variance. By minimizing the Schwarz Criterion one is trading off the lower residual variance from adding an additional coefficient against a penalty term that rises with the number of estimated coefficients. The strategy for selecting lag lengths in this paper is to (1) specify a maximum lag length; (2) assume that all independent variables in each equation have the same lag length; and (3) compute the Schwarz value for all possible lag length combinations. The resulting lag lengths for several variants of a basic five variable model are presented in the Appendix. Of special interest is the price equation for the AVAR model, which is

$$p_t = \mu_p + \sum_{j=1}^{m_d} \beta_{j,p} p_{t-j} + \sum_{v \neq p} \sum_{j=1}^{m_i} \beta_{j,v} X_{v,t-j} + \xi_t \tag{4}$$

where the number of lags m_d of the dependent variable is three and the number of lags m_i of each independent variable is one.

Forecast error statistics from representative VAR models are presented in Tables 1 and 2; a detailed account of the models' construction and the data used is given in the Appendix. Unless otherwise noted, each model contains five U.S. time series: real GNP, the GNP implicit price deflator, the monetary base, the manufacturing capacity utilization rate, and the 90-day Treasury-bill rate. Two models illustrate the basic result of relatively poor inflation forecasts. The model labeled AVAR is identical to one described in Webb (1985), except that the lag lengths are set by the simpler procedure described above. The model labeled BVAR uses Bayesian "priors" that have been advocated by Litterman (1984) to effectively limit the model's number of parameters that need to be estimated.

FORECASTING PROCEDURE

A rolling regression procedure was used to simulate forecasts to compare with data actually observed through 1990 Q4. Coefficients in each model were first estimated based on actual data from 1952 Q2 to 1977 Q1; one-quarter-ahead forecasts were made for each variable, which were then used to prepare forecasts for the next quarter, and so forth up to eight quarters ahead.[3] Each model's coefficients were then reestimated based on data from 1952 Q2 to 1977 Q2, and forecasts were again produced for each variable up to eight quarters ahead. The procedure was repeated through 1990 Q3. There were accordingly 100 observations on which the first estimate was based, 55 one-quarter-ahead forecasts, and 48 eight-quarter-ahead forecasts. Each forecast was compared with actual values and error statistics were calculated. An error is simply the actual value minus the predicted value. The square root of the mean squared error (RMSE) was then calculated for all available forecasts.

Exhibit 1 {place here} contains RMSE values for the levels of the interest rate and percentage changes of real GNP and the implicit deflator. For the latter two variables the columns labeled "Single Quarter Forecasts" were derived from percentage changes from the preceding quarter stated as a compound annual rate; the column labeled "Cumulative Forecasts" was derived from the percentage change over four quarters. The forecast horizon is the number of quarters beyond the latest data that were used to estimate the coefficients for the model. Thus for a one-quarter-ahead forecast for 1977 Q2, only data referring to 1977 Q1 and previous quarters would be used; that same data would also produce a two-quarter-ahead forecast for 1977 Q3, and so forth.

RMSEs are useful for giving a quick view of model accuracy. Another way to view the same data is presented with Theil U statistics in Exhibit 2. {Place here} Those values simply represent the ratio of the RMSE described above to the RMSE of a forecast of no change from the previous period. As with RMSEs, smaller U values represent more accurate forecasts; in addition, values greater than 1.0 indicate a forecast of little value under most loss functions.

BASIC RESULTS

The U Statistics in Exhibit 2 confirm that the inflation forecasts from the AVAR model are relatively inaccurate. While forecasts of the T-bill rate are similar or slightly worse than a no-change forecast, real GNP forecasts are substantially better. Inflation forecasts, however, are substantially worse. The BVAR model embodies a substantially different strategy for reducing a VAR model's parameterization. While its inflation forecasts are more accurate than the AVAR model, its single-quarter inflation forecasts are either worse than or not significantly better than a no-change forecast at each horizon.[4] Its cumulative inflation forecast is much better than a no-change forecast. The BVAR is less accurate than the AVAR, however, for GNP and interest rate forecasts.[5]

A more formal comparison of model and no-change forecasts can be made by testing the hypothesis that a series of forecast errors from a model is not significantly different from the series of errors that would result from a no-change forecast. Diebold and Mariano (1991) have proposed such a test that has several desirable properties; perhaps most important for this paper, it is valid even if the two series of forecast errors are contemporaneously correlated or if either series has significant autocorrelation. The DM test statistic is calculated from autocovariances of the difference in squared errors[6] from two forecasts, and is asymptotically normally distributed.

For each model listed in Exhibits 1 and 2, the inflation forecasts at each horizon were compared with no-change forecasts. DM statistics were calculated and are presented in Exhibit 3 {place here}; negative values indicate that the average squared error from the model was larger than the squared error of a no-change forecast. For the AVAR model, inflation forecasts at each horizon were significantly worse than the no-change forecasts. For the BVAR, forecasts one quarter ahead were also significantly worse than the no-change forecast, but were not significantly different at two, three, and four quarter horizons. The four-quarter cumulative forecast was significantly more accurate than the no-change comparison.

There are many possible explanations for the poor performance; only a few can be examined in a single article. Any small macroeconomic model omits variables that could be important, and there is certainly a long list of omitted variables that might affect prices. While examination of potential additions will be left for future research, poor choices may have been made in choosing the five variables included in the model. To examine that possibility, two additional models were used to produce simulated forecasts. One, labeled AVAR-M2, substitutes the M2 monetary aggregate for the monetary base. The rationale is that many researchers have documented a relationship between M2 and prices.[7] Another, labeled AVAR-CPI, substitutes the Consumer Price Index for the GNP implicit price deflator, on the grounds that movements in the deflator reflect not only price changes but also changes in the relative quantities of goods produced. In contrast, the CPI has fixed weights for lengthy intervals and is a closer approximation to the type of price index most analysts would prefer.

As indicated in Exhibit 1, substituting M2 for the monetary base failed to improve inflation forecasts and also produced less accurate forecasts for other variables. At each forecasting horizon the inflation forecasts were significantly worse than the no-change comparison.

The results from substituting the CPI for the implicit deflator are slightly better. The U statistic for the inflation term fell below unity at the shorter horizons in the table, as well as for the four-quarter cumulative forecast. The GNP and interest rate forecasts were slightly worse than in the original model.

A final variation is to simulate forecasts from a six-lag UVAR as a check on the conventional wisdom that substantially reducing the number of estimated coefficients will normally improve the accuracy of VAR forecasts. The results for prices were surprisingly accurate (to the author, at least); these results should not have been too surprising, however, in light of Lupoletti and Webb (1986), who found simulated UVAR inflation forecasts at all but a one-quarter horizon to be competitive with those from major forecasting services.

Attempting to isolate the reason for the UVAR model's greater accuracy, a hybrid model was simulated. The intuition here is that since inflation rates are highly persistent, long lags might be especially useful. The AVAR specification was adopted for every equation except the price equation, and the unrestricted six-lag version was used for prices. The results were roughly between the AVAR and UVAR in forecast accuracy. Another hybrid model was then simulated, using unrestricted lags in the equations for prices and the monetary base. The results are shown in the table, labeled A/UVAR. This model produced the most accurate longer-term inflation forecasts, with little penalty for other variables.

The main result of this section is that the VAR models generated price forecasts that, for most horizons, were significantly worse than simply predicting no change. In order to isolate potential problems, the price equation from the AVAR and A/UVAR models is examined more closely below.

SPECIFICATION TESTS FOR PRICE EQUATIONS

The price equations from two VAR models will be examined more closely in this section. Equation (5) is from the AVAR model with shorter lag lengths, and the other is equation (6) with longer lag lengths. Both equations are reprinted below.

$$p_t = \mu_p + \sum_{j=1}^{3} \beta_{j,p} p_{t-j} + \sum_{v \neq p} \sum_{j=1}^{1} \beta_{j,v} X_{v,t-j} + \xi_t \tag{5}$$

$$p_t = \mu_p + \sum_{v=1}^{5} \sum_{j=1}^{6} \beta_{j,v} X_{v,t-j} + \varepsilon_t \tag{6}$$

Residuals from both equations were first tested for serial correlation. The specific test[8] is a Lagrange multiplier test that takes into account the presence of lagged values of the dependent variable and little prior knowledge of the exact form of serial correlation. The procedure is to first estimate the price equation and its residuals and then add m lagged values of the residuals to the equation before reestimating it. An F test on the significance of the lagged values is asymptotically valid for a null hypothesis of no serial correlation and an alternative hypothesis of either AR(m) or MA(m) errors.

As the first line in Exhibit 4 {place here} indicates, the null hypothesis of no serial correlation is rejected for equation (5) with short lags. For equation (6) with unrestricted lags, the null hypothesis is not rejected when the alternative is first order correlation, an unsurprising result with six lagged values included in the equation. With an alternative hypothesis of fifth order autocorrelation, however, the null hypothesis can be rejected.

The next test, for autoregressive conditional hetereoskedasticity (ARCH), is also a two-step procedure; the first step is also to estimate the price equation and its residuals. The second step is to regress the squared residual on a constant term and m lags of the squared residual. The number of observations times the R^2 statistic is chi-squared with m degrees of freedom under the null hypothesis of no ARCH. The null hypothesis is rejected for equation (5) with m=1, and is also rejected for equation (6) with m=5.

A final test is whether it is appropriate to estimate the price equation in first differences. A standard Dickey-Fuller test was used to examine the log-level price series, and the null hypothesis of the presence of a unit root was accepted. Similar test results for the series of first differences were ambiguous, however. As shown in Exhibit 4, either acceptance or rejection of the null hypothesis could occur, depending on the lag length of the differenced inflation rates.[9] Since there is no conclusive reason a priori to prefer one lag length to another, the choice of working with first or second differences of the price data is a close call. Since overdifferencing risks losing information that could be useful in forecasting, the basic models in this paper use the first difference of the implicit deflator.

FORECAST PERFORMANCE WITH MODIFIED MODELS

STATIONARITY AND POSSIBLE COINTEGRATION

The VAR models discussed above contained three variables in differences: the price level, the monetary base, and real GNP. Formal tests for stationarity have already been discussed for the price series. Dickey-Fuller tests also failed to reject the null hypothesis of nonstationarity for the monetary base, real GNP, and the interest rate, but did reject the null when data were differenced one time. The capacity utilization rate, which is stationary by construction, was not tested.

ARE THE VARIABLES COINTEGRATED? It is also possible that the equations in differences may be misspecified if there is a linear combination of those variables that is stationary. It is especially important to check the variables in this model since (1) other authors, for example Mehra (1991), have found that closely related series are cointegrated, and (2) theory suggests that the variables could be related by the quantity equation with interest-sensitive velocity and a money-multiplier relation between the monetary base and the money supply. If cointegration were to be found, then the use of an error correcting model might well improve forecast accuracy.

A cointegrating equation was therefore used to estimate the parameters of such a linear combination. If the residuals from that equation are not found to be nonstationary, the hypothesis of cointegration can be accepted.[10] A cointegrating equation for the four nonstationary variables was therefore estimated, and the results are displayed in Exhibit 4. An augmented Dickey-

Fuller test was used to test the null hypothesis that the residuals were nonstationary, which would imply that the series are not cointegrated. While the test result could possibly be affected by the lag length m, the value shown in the table is the one that maximizes the $\bar{R}^2$ statistic, and is also the shortest lag length for which the Ljung-Box Q statistic does not indicate significant serial correlation. The failure to reject the null hypothesis is consistent with no cointegration.

SHOULD THE INTEREST RATE BE DIFFERENCED? At this point it is useful to question the economic significance of the finding that the interest rate is nonstationary. It is well known that the Dickey-Fuller test is not powerful against a highly persistent alternative, such as a root of 0.98. And there is a reason that one would expect the interest rate series to be highly persistent. Goodfriend (1991) discusses theoretical and empirical work on central bank smoothing of nominal interest rates -- that is, daily changes in reserve supply that keep the federal funds rate within a narrow band that is only changed infrequently. Such smoothing could impart a high degree of persistence to even a quarterly average of a daily rate, as is used in this paper.

It may therefore be appropriate to treat the interest rate as stationary, as was done in the models presented earlier. A regression with the [illegible] valuable information. But if that assumption were wrong and the interest rate were actually a random walk, the regression in levels would be spurious and differencing would be appropriate.

In order to empirically examine which specification is more appropriate, lag lengths were reset in the A/UVAR model with the interest rates in differences; series of forecasts were then generated. The somewhat ambiguous results are shown in Exhibit 5 for the model labeled A/UVAR-RD. The interest rate forecasts from the latter model were slightly more accurate, but forecasts of GNP growth and inflation were less accurate. Those results are consistent with the notion that the information loss from differencing may be large enough to justify entering the interest rate in level form.

ANOTHER POSSIBILITY OF COINTEGRATION: Admitting the possibility that the interest rate and inflation series are nonstationary, could there be a stable "real" rate, that is, the nominal rate minus the quarterly inflation rate?[11] To test this possibility, it is not necessary to estimate a cointegrating equation since the coefficients are known to be one and minus one. A real rate series was therefore constructed; a Dickey-Fuller test, presented in Exhibit 4, rejects the null hypothesis of the presence of a unit root.

Given the stationary combination of two arguably nonstationary series, the next step is to construct a vector error correcting version of the A/UVAR model (VECM). The strategy used here was to difference the nominal rate and inflation series, and add the first lag of the constructed real rate series to each equation. The resulting price equation is

$$\Delta^2 p_t = \mu_p + \sum_{v=1}^{k} \sum_{j=1}^{m} \beta_{j,v} X_{v,t-j} + \gamma rr_{t-1} + \eta_t \tag{7}$$

where p is the log of the implicit deflator, rr is the error correcting term, that is the nominal rate minus the inflation rate, and the variables in X are altered to include the first differences of the interest rate and inflation rate. Lag lengths were reset to minimize the Schwarz Criterion. Forecasts were then generated, with summary statistics given in Exhibit 5. The inflation values indicate that the VECM forecasts are much worse than the standard A/UVAR model. It appears that the information lost from differencing the inflation series was substantial, while the value of including the level of the real rate was not large.

One final check of possible cointegration was made using the multivariate test proposed by Watson (1992). In this test the null hypothesis is the existence of one cointegrating vector, the real interest rate; the alternative is the existence of an additional cointegrating vector. The test is a likelihood ratio, and in this case involves comparing the largest eigenvalue of a matrix computed from the appropriate VECM with critical values that were computed from the statistics' asymptotic chi-squared distributions. In this case, the largest eigenvalue was 9.7, well below the critical value of 20.4 that would indicate rejection of the null hypothesis at the 10% level. This failure to reject the null is consistent with the results of the univariate tests above, and does not indicate that further analysis of possible cointegration would prove useful.

In short, reconsidering the stationarity of the variables and possible cointegration did not indicate a direction for improving the accuracy of inflation forecasts from the VAR models examined here.

POSSIBLE REGIME CHANGES

It is common to think of nonstationary behavior of an economic variable by analogy to a random walk with frequent small, permanent disturbances. Indeed, widely used statistical tests for nonstationarity are derived under the assumption of such a random walk as the null hypothesis. Other types of nonstationarity are also possible, however. An alternative that is pursued in this section involves large, infrequent shocks. Several authors have found that U.S. postwar inflation data appear to have been generated by a process with one or more discrete shifts.

Evans and Wachtel (1993) proposed a two-state Markov switching process for the CPI, and found that it explained some of the puzzles that are raised by the ex post bias often found in series of inflationary anticipations. Boschen and Talbot (1991) found evidence of unstable coefficients in regressions of inflation on several variables, notably including the growth of the monetary base, growth of real GNP, and the differenced T-bill rate. Balke and Fomby (1991) studied the GNP deflator from 1870 to 1988 and found four "level shifts" to the inflation rate; the two in postwar data were in 1968 and in 1983.[12]

The last finding provides statistical evidence that something important that affects inflation changed around the mid 1960s and early 1980s. An obvious possibility is that something about monetary policy changed. I find it plausible that (1) the President and Congress chose to tolerate higher inflation during the Viet Nam buildup for a variety of reasons, including raising revenues via "bracket creep" and the personal income tax;[13] (2) as long as this consensus held, monetary policy had an inflationary bias;[14] (3) this consensus was destroyed by the early 1980s;[15] and (4) monetary policy then included low inflation as an important goal. It is therefore possible to view monetary policy as making a discrete move toward more inflation at some point in the middle of the 1960s, with the monetary effects on prices becoming apparent by 1968; a discrete move toward disinflation occurred somewhat later and the inflation effects became apparent by 1983.

DATING REGIME CHANGES: What were the exact dates of these discrete moves? The strategy here will be to look for specific actions that do not fit the pattern of the Fed's usual behavior. It is possible to loosely characterize monetary policy since the Federal Reserve - Treasury Accord in 1951 as "leaning against the wind." That is, the Fed's day-to-day actions involved open market operations that varied the quantity of bank reserves in order to keep the federal funds rate within a narrow band. The funds rate band, in turn, was set in order to respond to pressing economic conditions. This often involved raising the funds rate when inflation was rising and unemployment relatively low, and lowering the funds rate when inflation was low and real growth weak. In addition, there were times during which unusually rapid or slow money growth would bolster the case for changing the funds rate target.

The Fed departed from that strategy in the 1960s; the background account in this paragraph is taken from Kettl (1986). In 1965 President Johnson substantially increased military action in Viet Nam, proposed domestic social legislation requiring increased spending, but resisted increasing nominal interest rates. In June 1965 the Fed's chairman William McChesney Martin learned that the Viet Nam buildup was larger than the administration was publicly admitting. In October Martin wrote to the President arguing for an immediate increase in interest rates. On December 5 the Fed raised the discount rate by 50 basis points, and "Johnson was furious. He and his advisers believed that the decision was precipitous .... The President saw the discount rate increase as a personally vindictive act."[16] The President and the Chairman met at the President's ranch in Texas later that month.

In 1966 real growth was a rapid 6.0 percent, the unemployment rate was a very low 3.7 percent, and the inflation rate (the change in the annual average CPI) rose from 1.6 in 1965 to 2.9 percent. A consistent application of leaning against the wind would have required increasing the funds rate until inflation was clearly checked. Although interest rates rose during the first part of the year, in the fourth quarter "Monetary policy promptly moved to relax the degree of reserve restraint."[17] The inflation rate was 3.1 percent in 1967, 4.2 percent in 1968, and 5.5 percent in 1969. Here is a clear departure from the previous leaning against the wind strategy, namely lowering interest rates, beginning in the fourth quarter of 1966, while inflation was rising and unemployment low.

The fourth quarter of 1966 was therefore the end of a low inflation period. By the end of the 1970s inflation was being described as "public enemy number one." That sentiment did not translate immediately into presidential support for a substantial change in monetary policy. In the lead paragraph of his 1980 Economic Report to Congress, President Carter asserted that higher oil prices were the major reason for rising inflation in 1979. In that twelve page statement, there are only two sentences that mention monetary policy. The most relevant is, "Monetary policy will have to *continue* firmly in support of the *same* anti-inflationary goals."[18] [Emphasis mine] In January 1981 the political party controlling the Presidency and the Senate changed. The discussion of monetary policy also changed substantially. For example, in the first annual report of the Reagan Administration's Council of Economic Advisers (1982), one encounters the following phrases: "Inflation is essentially a monetary phenomenon." p.75; "The appropriate policy for reducing the inflation rate is a decrease in the rate of money growth." p.76; "The Administration expects that the Federal Reserve will achieve an orderly reduction in the trend of money growth to a *noninflationary* rate." p.64 [Emphasis mine].

Monetary growth was high and variable in the 1970s and also in 1980; for example, M1 grew at a 16 percent annual rate between May and November of 1980. In 1981, however, "growth in M1-B adjusted for shifts into NOW accounts was about 2 1/4 percent -- 1 1/4 percentage points below the lower end of its targeted range."[19] That behavior of the main intermediate target of Fed policy, shift-adjusted M1-B, was substantially different from what had been seen in the past decade.

Turning to specific actions, in the first quarter of 1981 the unemployment rate was 7.4 percent, compared to an average 7.0 percent in 1980 and 5.8 percent in 1979. The trend in real activity was difficult to interpret in light of the monetary volatility in the last year as well as the imposition and removal of credit controls in 1980. During the second quarter of 1981 shift-adjusted M1-B was at or below the lower bound of the target range that the Fed had announced in February. Yet the federal funds rate rose by five full percentage points from April 1 to July 8.[20] Here is an extraordinary departure from previous behavior; the second quarter of 1981 is therefore the last of the inflationary period.[21]

ECONOMETRIC RESULTS: Based on the evidence discussed above, three periods are studied: an early low inflation period from 1952 Q2 to 1966 Q4; a middle inflationary period from 1967 Q1 to 1981 Q2; and a disinflationary period from 1981 Q3 to 1990 Q4. Separate regressions were run for each subperiod and the entire sample; the results are displayed in Exhibit 6.

Perhaps most striking is the complete failure of the restricted equation for the early period, with essentially no explanatory power from its regressors. Regressions for the middle and late periods appear to work somewhat better, at least as indicated by the usual summary statistics. For the whole period the sum of the coefficients on nominal variables, that is lagged prices, the interest rate, and the monetary base, is approximately unity. In the middle period, however, it is 1.26 while in the late period it is 0.80. The sum of coefficients on lagged prices rises substantially in the two later periods; the strong persistence of inflation is not evident in the early period. The coefficient on the monetary base is significantly different from zero only in the middle period.

These statistical results are consistent with the story of monetary regime changes.[22] There are several options when forecasting under changing regimes. Perhaps the simplest is to use a few dummy variables to allow some coefficients to abruptly shift. Based on the results summarized in Exhibit 6, 0-1 dummies were constructed for the middle and late periods, labeled Dm and Dl, respectively. In addition, the product of Dm and the monetary base is labeled Db, and the product of the implicit deflator and sum of Dm and Dl is labeled Dp. Dm, Dl, and one lagged value each of Db and Dp were added to equation (5), with the results also displayed in Exhibit 6. {place here} As might be expected, the apparent fit of the equation improved and the four dummy variables were each significant at conventional levels.

Diagnostic tests were again repeated and are displayed in Exhibit 6. The F test for serial correlation was repeated on the price equation for the entire sample. In contrast to the results presented in Exhibit 4, the null hypothesis of no serial correlation is not rejected at conventional levels. The test statistic for ARCH is also presented, and the hypothesis of no ARCH is again rejected at the one percent level. Finally, Dickey-Fuller test statistics were constructed for the inflation rate over the three intervals. In the early and middle periods the null hypothesis of a unit root is rejected at the one percent level. For the late period, the null is rejected at either the five or ten percent level, again depending on a lag length used in the test.

Adding the dummy variables to the price equation of the AVAR model substantially improved its forecasting performance, as shown in Exhibit 5. The modified AVAR model has by far the most accurate inflation forecasts at each horizon of any of the models considered in the paper, with the GNP forecasts remaining as accurate as any of the models considered. Adding the same dummy variables to the A/UVAR model slightly improved its inflation forecasts, although the AVAR-D model remained significantly more accurate. Neither model forecasts the interest rate well.

To put these figures in perspective, consider the root-mean-square errors of the ASA-NBER inflation forecasts from 1968 to 1990, taken from Zarnowitz and Braun, Table 5. The AVAR-D model was used to produce simulated forecasts for the same period. One-quarter-ahead forecasts from the VAR model were less accurate, with an RMSE of 1.48 percent versus 1.00 percent. Four-quarter cumulative forecasts from the VAR model were much more accurate, with an RMSE of 0.88 percent versus 1.92 percent. If taken at face value, the VAR's performance is competitive with actual forecasters of inflation over that interval. The major reason not to take the results at face value is the amount of experimentation that was used to construct the AVAR-D model. In addition, the model had the benefit of using revisions of GNP and implicit deflator data that were unavailable to the real-time forecasters.

CONCLUSION

Several small VAR models have been examined in this paper, with particular emphasis on inflation forecasts and the inflation equation of the models. Two models are of particular interest. One has unfashionably long, unrestricted lags in two equations. The other uses dummy variables to represent the political decision made in the 1960s to allow higher rates of inflation and the subsequent decision made in the early 1980s to lower the inflation rate.

The latter model produced the most accurate inflation forecasts of the models examined while its GNP forecasts retained their accuracy. That result suggests a resolution to the puzzle of relatively inaccurate inflation forecasts from VAR models; two monetary policy regime changes led to inaccurate inflation forecasts from models with constant coefficients. Moreover, either adding dummy variables or dividing the entire sample into three subperiods also removed serial correlation from the residuals of the price equation.

These results may be of interest to several groups. To anyone interested in price behavior, the improved performance of the price equation after an adjustment for temporal instability points out a danger of using constant coefficients over most of the postwar period. To users of small macro models, the finding that long, unrestricted lags led to an equation that worked well relative to a highly restricted equation suggests that long, unrestricted lag lengths should not be rejected out of hand. Students of monetary policy may find the dating of regime changes of interest. The finding that possible nonstationarity of the inflation rate over the postwar period is not apparent in the three subperiods of consistent monetary policy may be of interest to empirical macroeconomists concerned about potential nonstationarity in other contexts. Finally, if one wishes to forecast inflation, using the admittedly ad hoc dummy variables may be preferable to ignoring the monetary regime changes altogether.

Several directions for future research are also evident. First, do the results that are presented above overstate the probable accuracy of current inflation forecasts, due to too much experimentation? Of course, new data over time will reveal whether the post-sample performance of these models is in line with those results. Also, despite the experimentation there has been a basic stability in the model structure. Since 1984 the author has published results from VAR models with the same variables, with the same starting date for regressions, and with the same choices for differencing.[23] Changes have been limited to different lag lengths and the addition of the dummy variables for the two shifts in monetary policy.

This paper views monetary policy changes as being responsible for large, persistent shifts in the inflation process that several authors have identified. Are there other candidates such as energy prices that are equally plausible? And if the monetary policy explanation is accepted, are the suggested dates of regime change robust? One approach would be to estimate a structural relation between instruments and goals of monetary policy and examine its stability in the neighborhood of the dates of the suggested changes.

Residuals from the best performing price equation still displayed ARCH, and that specification failed to explain inflation during the early subperiod. It is therefore apparent that this model, like many other small macro models, might benefit from additional variables that help predict inflation rates. The challenge will be to narrow the field, given the large number of variables that analysts have used with apparent success in price equations in the past.

APPENDIX: THE DATA AND MODELS

The following data series, with Citibase mnemonic in parentheses, were used in this paper: P, the implicit price deflator for gross national product (GD); Y, real gross national product (GNP82); M, the monetary base as estimated by the Federal Reserve Bank of St. Louis (FMBASE); CU, the capacity utilization rate in manufacturing (IPXMCA); R, the secondary market yield on three month treasury bills (FYGM3); CPI, the consumer price index for all urban consumers (PUNEW), and the M2 monetary aggregate after 1959 (FM2). All except the interest rate were seasonally adjusted by the agency compiling the data. Natural logarithms were taken of each data series except the interest rate and the capacity utilization rate. Data were the latest revisions maintained by Citibase on July 19, 1991. Pre-1959 M2 data were obtained from Robert Hetzel; see Hetzel (1989) for further information on its construction.

The table below describes each model in the paper. Each model is a collection of equations that are individually described. The column labeled DEP VAR contains the dependent variable for each equation. The column labeled DIFF? contains a Y for differenced series, N for levels, and 2 for a series differenced twice. The number of lagged terms for the dependent variable and the common lag length for all the independent variables are given in the next two columns. The final column notes if an equation contained dummy variables as described in the final section, or RR, the difference between the nominal interest rate and the inflation rate; a constant term was also included in each equation.

Model Descriptions

MODEL	DEP VAR	DIFF?	# OWN LAGS	# LAGS OF IND VARS	OTHER TERMS
A/UVAR	P	Y	6	6	
	Y	Y	1	1	
	M	Y	6	6	
	C	N	2	1	
	R	N	6	1	
A/UVAR-D	P	Y	6	6	d_m d_l d_p d_b
	Y	Y	1	1	
	M	Y	6	6	
	C	N	2	1	
	R	N	6	1	
A/UVAR-RD	P	Y	6	6	
	Y	Y	1	1	
	M	Y	6	6	
	C	N	2	1	
	R	Y	2	1	
AVAR	P	Y	3	1	
	Y	Y	1	1	
	M	Y	3	2	
	C	N	2	1	
	R	N	6	1	
AVAR-CPI	CPI	Y	3	1	
	Y	Y	1	1	
	M	Y	3	2	
	C	N	2	1	
	R	N	6	1	
AVAR-D	P	Y	3	1	d_m d_l d_p d_b
	Y	Y	1	1	
	M	Y	3	2	
	C	N	2	1	
	R	N	6	1	
AVAR-M2	P	Y	3	1	
	Y	Y	1	1	
	M2	Y	1	2	
	C	N	2	1	
	R	N	3	1	
BVAR[24]	P	Y	6	6	
	Y	Y	6	6	
	M	Y	6	6	
	C	Y	6	6	
	R	Y	6	6	
VECM	P	2	6	6	RR
	Y	Y	1	1	RR
	M	Y	6	6	RR
	C	N	1	1	RR
	R	Y	5	1	RR

EXHIBIT 1
Forecast Error Statistics from Several VAR Models
Root Mean Square Errors

Model	Variable	Single Quarter Forecasts Horizon: 1Q	2Q	4Q	Cumulative Forecasts 4Q
AVAR					
	IPD	1.57	1.92	2.62	1.84
	GNP	3.40	3.07	3.50	1.58
	RTB	1.20	1.95	2.44	
BVAR					
	IPD	1.58	1.59	1.79	1.11
	GNP	3.81	3.75	4.21	1.92
	RTB	1.24	2.03	2.69	
AVAR-M2					
	IPD	1.86	2.32	3.17	2.30
	GNP	3.75	3.41	3.84	2.15
	RTB	1.26	2.05	2.60	
AVAR-CPI					
	CPI	1.91	2.56	3.22	2.16
	GNP	3.40	3.24	3.58	1.80
	RTB	1.24	2.04	2.60	
A/UVAR					
	IPD	1.69	1.64	1.73	1.11
	GNP	3.40	3.09	3.60	1.60
	RTB	1.20	1.97	2.50	

Note: Model construction and data sources are described in detail in the Appendix. Variable abbreviations include the quarterly average level of RTB, the 90-day Treasury-bill rate, and annualized rates of change from the previous quarter of GNP, real gross national product; IPD, the GNP implicit price deflator; and CPI, the consumer price index. The numerical entries are root-mean-squared error statistics described in the text, covering synthetic forecasts from *1977 Q2* to *1990 Q3*.

EXHIBIT 2
Forecast Error Statistics from Several VAR Models
Theil U Statistics

Model	Variable	Single Quarter Forecasts Horizon: 1Q	2Q	4Q	Cumulative Forecasts 4Q
AVAR					
	IPD	1.05	1.22	1.44	1.40
	GNP	0.75	0.63	0.66	0.47
	RTB	1.00	1.08	1.04	
BVAR					
	IPD	1.06	1.01	0.98	0.85
	GNP	0.84	0.77	0.80	0.58
	RTB	1.03	1.12	1.15	
AVAR-M2					
	IPD	1.25	1.46	1.74	1.74
	GNP	0.83	0.70	0.73	0.65
	RTB	1.05	1.13	1.11	
AVAR-CPI					
	CPI	0.85	0.92	1.02	0.96
	GNP	0.75	0.66	0.68	0.54
	RTB	1.03	1.13	1.11	
A/UVAR					
	IPD	1.13	1.04	0.95	0.84
	GNP	0.75	0.63	0.68	0.48
	RTB	1.00	1.09	1.06	

Note: Model construction and data sources are described in detail in the Appendix. Variable abbreviations include the quarterly average level of RTB, the 90-day Treasury-bill rate, and annualized rates of change from the previous quarter of GNP, real gross national product; IPD, the GNP implicit price deflator; and CPI, the consumer price index. The numerical entries are Theil U statistics described in the text, covering synthetic forecasts from 1977 Q2 to 1990 Q3.

EXHIBIT 3

VAR Inflation Forecasts Compared to No-Change Forecasts

Model	Variable	Single Quarter Forecasts Horizon: 1Q	2Q	4Q	Cumulative Forecasts 4Q
AVAR					
	U Statistic	1.05	1.22	1.44	1.40
	DM Statistic	-3.7	-11.7	-11.6	-5.2
	Significance, %	<0.1	<0.1	<0.1	<0.1
BVAR					
	U Statistic	1.06	1.01	0.98	0.85
	DM Statistic	-3.2	-0.2	0.63	2.4
	Significance, %	0.1	>10	>10	1.7
AVAR-M2					
	U Statistic	1.25	1.46	1.74	1.74
	DM Statistic	-12.8	-18.0	-10.0	-4.9
	Significance, %	<0.1	<0.1	<0.1	<0.1
AVAR-CPI					
	U Statistic	0.85	0.92	1.02	0.96
	DM Statistic	14.5	7.3	-1.0	0.9
	Significance, %	<0.1	<0.1	>10	>10
A/UVAR					
	U Statistic	1.13	1.04	0.95	0.84
	DM Statistic	-6.1	-1.2	1.6	2.2
	Significance, %	<0.1	>10	>10	2.9

Note: Model construction and data sources are described in detail in the Appendix. Synthetic forecasts inflation from 1977 Q2 to 1990 Q4 are compared with no-change forecasts. The U Statistic is the ratio the root-mean-squared error of the model forecast to that of a no-change forecast. The DM statistic tests the null hypothesis that the model and no-change forecast have equal accuracy; negative values indicate that the sum of squared forecast errors is larger for the model forecast.

EXHIBIT 4
Specification Tests for Price Equations

Equation (5) $p_t = \mu_p + \sum_{j=1}^{3} \beta_{j,p} p_{t-j} + \sum_{v \neq p} \sum_{j=1}^{1} \beta_{j,v} X_{v,t-j} + \xi_t$

Serial correlation test: F(1,145) = 3.93; Significance level = .049.

ARCH test: $\chi^2(1)$ = 5.13; Significance level = .024.

Equation (6) $p_t = \mu_p + \sum_{v=1}^{5} \sum_{j=1}^{6} \beta_{j,v} X_{v,t-j} + \varepsilon_t$

Serial correlation test: F(5,114) = 2.48; Significance level = .036.

ARCH test: $\chi^2(5)$ = 14.64; Significance level = .012.

Dickey-Fuller test for a unit root $Z_t = \mu + \sum_{j=1}^{m} \beta_j \Delta Z_{t-j} + \rho Z_{t-1} + e_t$

Price Level ($Z_t = P_t$): m=2; $\hat{\tau}_\mu(\rho=1)$ = 0.80; 10% sig. level = -2.58;

Differences ($Z_t = \Delta P_t$): m=1; $\hat{\tau}_\mu(\rho=1)$ = -3.42; 5% sig. level = -2.89;

Differences ($Z_t = \Delta P_t$): m=5; $\hat{\tau}_\mu(\rho=1)$ = -2.06.

"Real" Rate ($Z_t = R_t - (p_t - p_{t-1})$): m=2; $\hat{\tau}_\mu(\rho=1)$ = 14.1.

Cointegrating equation $P_t = 1.29 + .83M_t - .15Y_t + .016R_t + \hat{u}_t$

Augmented Dickey-Fuller test on residuals from cointegrating equation:

$$\Delta \hat{u}_t = -\pi \hat{u}_{t-1} + \sum_{j=1}^{5} \beta_j \Delta \hat{u}_{t-j}$$

t (π=0) = 3.12; 10% level = 3.89

Note: This significance level is from Engle and Yoo (1987).

EXHIBIT 5
Forecast Error Statistics from Several Models
Theil U Statistics

Model	Variable	Single Quarter Forecasts Horizon: 1Q	4Q	8Q	Cumulative Forecasts 4Q
A/UVAR					
	IPD	1.13	0.95	1.06	0.84
	GNP	0.75	0.68	0.65	0.48
	RTB	1.00	1.06	1.03	
A/UVAR-RD					
	IPD	1.19	1.02	0.98	0.94
	GNP	0.81	0.75	0.61	0.69
	RTB	0.98	0.98	1.03	
VECM					
	IPD	1.30	1.55	2.09	1.49
	GNP	0.80	0.73	0.61	0.71
	RTB	0.95	1.08	1.20	
A/UVAR-D					
	IPD	1.16	0.69	0.65	0.65
	GNP	0.75	0.68	0.65	0.48
	RTB	1.00	1.05	1.02	
AVAR					
	IPD	1.05	1.44	1.54	1.40
	GNP	0.75	0.66	0.64	0.47
	RTB	1.00	1.04	1.00	
AVAR-D					
	IPD	0.83	0.67	0.56	0.58
	GNP	0.75	0.66	0.64	0.47
	RTB	1.00	1.04	1.00	

Note: Model construction and data sources are described in detail in the Appendix. Variables include the quarterly average level of RTB, the 90-day Treasury-bill rate, and annualized rates of change from the previous quarter of GNP, real gross national product; and IPD, the GNP implicit price deflator. The numerical entries are Theil U statistics described in the text, *covering* synthetic forecasts from 1977 Q2 to 1990 Q3.

EXHIBIT 6
Regression Results for Several Time Periods

1952 Q2 to 1966 Q4

$$\hat{p}_t = \underset{(0.06)}{0.28} - \underset{(-0.54)}{0.08}p_{t-1} + \underset{(0.51)}{0.08}p_{t-2} + \underset{(0.72)}{0.11}p_{t-3} + \underset{(0.24)}{0.07}r_{t-1} + \underset{(0.28)}{0.02}c_{t-1} - \underset{(-0.01)}{0.01}m_{t-1} + \underset{(0.76)}{0.05}y_{t-1}$$

$\bar{R}^2 = -0.08$ $\hat{\sigma} = 1.85$ $F(1,149) = 0.17$ $\chi^2(1) = 3.48^{***}$

$\hat{\tau}_\mu = -7.90^{*}$ $(m=0)$

1967 Q1 to 1981 Q2

$$\hat{p}_t = \underset{(-0.54)}{-2.78} + \underset{(2.30)}{0.30}p_{t-1} - \underset{(-0.28)}{0.04}p_{t-2} + \underset{(0.27)}{0.04}p_{t-3} + \underset{(2.56)}{0.33}r_{t-1} + \underset{(0.26)}{0.02}c_{t-1} + \underset{(4.87)}{0.60}m_{t-1} - \underset{(-1.52)}{0.08}y_{t-1}$$

$\bar{R}^2 = 0.57$ $\hat{\sigma} = 1.59$ $F(1,148) = 2.42$ $\chi^2(1) = 2.31$

$\hat{\tau}_\mu = -3.64^{*}$ $(m=0)$

1981 Q3 to 1990 Q4

$$\hat{p}_t = \underset{(-1.54)}{-8.87} + \underset{(1.16)}{0.21}p_{t-1} + \underset{(0.53)}{0.09}p_{t-2} + \underset{(1.15)}{0.20}p_{t-3} + \underset{(1.07)}{0.20}r_{t-1} + \underset{(1.68)}{0.10}c_{t-1} + \underset{(1.02)}{0.10}m_{t-1} - \underset{(-0.21)}{0.15}y_{t-1}$$

$\bar{R}^2 = 0.51$ $\hat{\sigma} = 1.06$ $\hat{\tau}_\mu = -2.63$ $(m=1)$ $F(1,28) = 0.45$ $\chi^2(1) = 0.46$

$\hat{\tau}_\mu = -2.63^{***}$ $(m=1)$ $\hat{\tau}_\mu = -2.95^{**}$ $(m=2)$

1952 Q2 to 1990 Q4

$$\hat{p}_t = \underset{(-1.42)}{-3.84} + \underset{(6.38)}{0.30}p_{t-1} + \underset{(2.89)}{0.23}p_{t-2} + \underset{(2.71)}{0.22}p_{t-3} + \underset{(0.07)}{0.005}r_{t-1} + \underset{(1.54)}{0.05}c_{t-1} + \underset{(2.95)}{0.17}m_{t-1} - \underset{(-0.59)}{0.22}y_{t-}$$

$\bar{R}^2 = 0.59$ $\hat{\sigma} = 1.75$ $F(1,145) = 3.93^{**}$ $\chi^2(1) = 5.13^{**}$

EXHIBIT 6
(Continued)

1952 Q2 to 1990 Q4 with Dummies

$$\hat{p}_t = \underset{(-0.51)}{-1.29} - \underset{(-0.45)}{0.05p_{t-1}} + \underset{(0.29)}{0.02p_{t-2}} + \underset{(0.82)}{0.06p_{t-3}} + \underset{(2.34)}{0.21r_{t-1}} + \underset{(1.16)}{0.04c_{t-1}} + \underset{(0.30)}{0.02m_{t-1}} - \underset{(-0.44)}{0.02y_{t-1}}$$

$$- \underset{(-2.66)}{2.11d_m} - \underset{(-2.00)}{1.32d_l} + \underset{(2.53)}{0.38d_p} + \underset{(3.61)}{0.42d_b}$$

$\bar{R}^2 = 0.68$ $\hat{\sigma} = 1.56$ $F(1,141) = 0.25$ $\chi^2(1) = 23.4^*$

Significance levels: 1%, *; 5%, **; 10%, ***

Note: For each equation t-statistics are in parentheses. Symbol definitions are as follows: p is the inflation rate, t is a time subscript, r is the level of the 3-month T-bill rate, c is the manufacturing capacity utilization rate, m is the percentage change of the quarterly average monetary base, y is the percentage change of real GNP, dm is a dummy variable that is unity from 1967 Q1 to 1981 Q2 and zero otherwise, dl is a dummy variable that is unity from 1981 Q3 to 1990 Q4 and zero otherwise, dp is the product of p and dm+dl, and db is the product of dm and m. The $\hat{\tau}_\mu$ statistic allows a Dickey-Fuller test of the hypothesis of a unit root in the dependent variable. The F statistic allows a test of the null hypothesis that serial correlation is zero. The chi-squared statistic allows a test of the null hypothesis of no ARCH.

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ENDNOTES

1. Doan (1990), p. 8-16.

2. Why was the Schwarz Criterion used instead of some other statistic? One reason, which is only applicable for this paper, is simply to have a sharp difference between the restricted and unrestricted models. More generally, Yi and Judge (1988) studied the asymptotic performance of three widely used statistics for model selection. Only the Schwarz Criterion excluded irrelevant variables with a probability approaching one as the sample size increased.

3. These would be referred to as early quarter forecasts, since they assume knowledge of the previous quarter's implicit deflator and GNP values, which are now first released near the end of the first month of a quarter. In real time, a forecaster would also have other valuable information by the time those values are released, such as some values in the current quarter for interest rates and the monetary base.

4. Forecasts from one to eight quarters ahead were examined, although only a few horizons are shown in the table. The discussion in the text refers to all periods, whether or not included in the table.

5. These BVAR model results are based on a model in which real GNP, the implicit price deflator, and the monetary base are differenced. Many users of BVARs, however, prefer to use levels and trend terms. In other words, they prefer to assume trend stationarity rather than difference stationarity. To see if these results are sensitive to that assumption, the BVAR model was also simulated with all variables in levels and with a time trend in the equations. The results of simulated forecasts were generally worse, especially for the inflation rate.

6. While this paper uses squared errors, other functions of the error series would also be valid.

7. A particularly well-known example is Hallman, Porter, and Small (1989).

8. For a discussion of this particular test see Godfrey (1988), section 4.4.

9. The shorter lag length was chosen to minimize the Schwarz Criterion. A longer lag was also examined to check the robustness of the test to the lag length. This was particularly important for prices since earlier work, Webb (1988), had found that the results of Dickey-Fuller tests for unit roots in the CPI series were also dependent on the lag length.

10. Engle and Granger (1987) is the classic reference on the subject.

11. For a proper ex post real rate, the 3-month nominal rate R would be the value at the beginning of the quarter, the log price level P would be the value at the end of the quarter, and the real rate would be $R_t - (P_t - P_{t-1})$. The measures for the nominal rate and the price level that are actually used in this paper are

quarterly averages. Of course, one could also argue that an ex ante real rate would be preferable.

12. It is interesting to note that they also applied their procedure to real GNP growth over the same period and did not find any level shift.

13. See, for example, Hetzel (1990), who emphasizes the interaction of inflation and a nonindexed tax code. In 1974 alone he estimates that an eleven percent inflation rate raised the growth in tax revenues to seventeen percent despite falling real personal income.

14. While the Federal Reserve has considerable independence in its day to day operations, if it were to pursue goals outside a political consensus for very long, legislation putting permanent restrictions on the Fed could be enacted. Since officials would most likely not wish to see such legislation enacted, as a practical matter one would not expect to see the Fed continue to pursue goals that the President and Congress opposed.

15. The Economic Recovery Tax Act of 1981 included substantial indexing of the personal income tax for inflation, thereby reducing the government's revenue gains from inflation. According to Steurle (1991), "The major individual reform instituted in 1981 was not the direct reduction in tax rates, but the establishment of indexing of tax brackets .... Eventually, indexing will dominate all other provisions of the 1981 Act."

16. Kettl, p. 104.

17. Martin (1967), p. 215. The phrase "lowering the degree of reserve restraint" can be translated as lowering the fed funds rate.

18. The other is "The October actions of the Federal Reserve Board to change the techniques of monetary policy helped moderate inflationary expectations which had been partly responsible for the pressure on the [foreign exchange value of the] dollar."

19. Volker (1982) p. 129.

20. For an account of specific Fed actions during this period see Cook (1989).

21. Some analysts prefer to date the monetary regime change as October 6, 1979, the time of a Fed announcement of a major change in operating procedures. Arguing against that date are (1) at the time, the President did not publicly support a strong, disinflationary monetary policy, preferring instead to focus on wage-price guidelines, energy conservation, and the risks of monetary policy being too tight; (2) an important political incentive for inflation, the lack of indexing of the personal income tax, was not removed until 1981; and (3) monetary growth in 1980 was not consistent with a shift to a disinflationary monetary policy.

22. The statistical hypothesis of structural stability could of course be formally tested with a standard Chow test. That test, however, is invalid when the full-sample regression has residuals that display ARCH, as in this case. It

is however possible to construct a likelihood ratio test of the joint hypothesis of constant coefficients and constant residual variance against the alternative of changing coefficients and/or changing residual variance. The LR statistic in this case has a chi-squared (18) distribution; the calculated LR value, 43.45, indicates the null hypothesis is rejected at the 1% level.

23. See Webb (1984, 1985, 1991) and Lupoletti and Webb (1986).

24. An important part of the BVAR specification procedure is to set "hyper-parameters" that could in principle be used to impose prior beliefs on the data. Here these parameters were chosen to minimize the log-determinant of the variance-covariance matrix constructed from one-quarter-ahead forecast errors for the model. The resulting choices are summarized in the RATS statement

```
SPECIFY(type=symmetric,decay=.5,tight=.6) .9
```

(see Doan, ch. 8.8 for further details).