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THE QUANTITATIVE SIGNIFICANCE OF THE LUCAS CRITIQUE

Preston J. Miller and William Roberds

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Recent papers by Litterman [1984], Sims [1982 and 1986], and Doan-Litterman-Sims (DLS) [1984] advocate the use of Bayesian-restricted vector autoregressive models (BVARs) for policy analysis. The authors suggest using the BVARs to generate forecasts which are conditional on assumed future paths of policy variables. Using macroeconometric models in this way would seem to violate the Lucas critique.[1/] But while those authors are aware of the Lucas critique and even acknowledge its logical validity, they question its quantitative significance.

In this paper we attempt to determine the quantitative significance of the Lucas critique. We examine the stability of coefficients in a BVAR following two recent macro policy changes and assess the accuracy of forecasts conditional on policy variables in arbitrary periods. For the two policy changes our evidence suggests that unpredictable coefficient changes were large and were primarily responsible for sizable prediction errors in nonpolicy variables. For the accuracy of forecasts in arbitrary periods our evidence suggests that while the DLS conditional forecasting methodology may capture some of the effects of policy changes, it does not capture the majority of them.

The Lucas critique maintains that the coefficients of a macroeconometric model will change when there is a change in the rule which determines policy actions based on the state of the economy. The reasoning seems unassailable. The relationships in a macroeconometric model are aggregates of individual decision rules. In a stochastic, dynamic environment, the decisions of optimizing agents depend on expectations of those future policy actions that affect their budget sets. A change in the policy rule will change individuals' expectations of future policy actions and will, therefore, change the way individuals make decisions based on current information. This change in individual decision rules then translates into changes in the coefficients of aggregate relationships in macroeconometric models.

While Doan, Litterman, and Sims don't quarrel with the logic of the Lucas critique, they do question its relevance. They argue that most changes in policy that have occurred and that are usually contemplated are not like Lucas's once-and-for-all changes in policy rules. Rather, they argue that policy changes are like the drawings of residuals under a given policy rule. Since policy changes tend to be small deviations from existing policy, Sims argues that the Lucas critique at most amounts to small non-linearities in a BVAR which can be accommodated by specifying time-varying coefficients.2/ Sims goes on to state that:

> . . . policy rules in the relevant sense of that term have not changed frequently or by large amounts. The large forecast errors of recent years do not seem to be attributable mainly to shifts in the structure of predictive equations. Statistical models allowing for drift in predictive structure estimate best when the change in that structure is assumed to be slow, so that recent large predictive errors are interpreted as large random shocks to the equations, not mainly as the effect of parameter changes.3/

Given that interpretation, the DLS conditional forecasting procedure seems to be a reasonable way to forecast the effects of policy changes.

In this paper we attempt to check whether Doan, Litterman, and Sims are right. We focus first on two recent policy changes: the fall 1979 change in the FOMC operating procedures and the fall 1981 Reagan budget initiatives. We begin by describing the BVAR we use to analyze these policy changes. We next examine some empirical evidence on the magnitude of the policy changes in order to determine whether they seem more like policy rule changes or like random drawings under given policy rules. While our evidence is not decisive, it does suggest that these changes are good candidates for rule changes. We then look for empirical evidence of coefficient changes following the policy changes. We find some striking evidence of coefficient changes, although the evidence is somewhat stronger following the change in monetary policy than following the change in budget policy.

We focus second on the accuracy of forecasts conditional on policy. If BVARs are able to predict the effects of policy changes, then forecasts conditional on actual future paths of policy variables should be more accurate than unconditional forecasts. Yet, we find only marginal improvement. The improvement, moreover, is only a small fraction of what could be obtained if the coefficient changes were known in advance. So here again coefficient changes predominate.

I. Construction of a BVAR

Our BVAR was constructed using the methodology described in Sims [1982] and Doan, Litterman, and Sims [1984].

A. Choice of Variables

We chose six post-war (1948:2-1986:1) U.S. quarterly macroeconomic series for our study: (the logarithm of) real GNP, the inflation rate as defined by differenced logs of the GNP deflator, the three-month T-bill rate, the trade-weighted value of the dollar, and two indicators of policy. The first of the policy series which we take as an indicator of current monetary policy is the ratio of outside money (the St. Louis adjusted monetary base) to total outside debt held by the public (the accumulated NIA deficit less Federal Reserve debt holdings). The second series which we take as an indicator of fiscal policy is the ratio of the NIA deficit net-of-interest to nominal GNP. Our choice of policy variables was motivated by the theoretical analyses of Wallace [1984] and Miller-Wallace [1985]. Our choice also was influenced by stationarity considerations, the predictive ability of the whole model, and the responses of the nonpolicy variables to policy shocks. A detailed description of the data series is given in Appendix A, and plots of the data series are displayed in Figures 1a-1f.

B. Specification Search

We considered a number of different specifications for our VAR forecasting model. Following DLS and Swamy and Tinsley

[1980], we allowed for explicit time variation in the parameters of the model.4/ Our estimation methodology was the usual "Bayesian" one of specifying initial first and second moments to offset the overparameterization inherent in VAR models. That is, the models we considered took the form

$$(1) \qquad y(t) = A_t(L)y(t-1) + c(t) + u(t)$$

where $y(t)$ is the time t observation on the vector of six macroeconomic variables, $A_t(L)$ is the time varying autoregressive polynomial in the lag operator L, $c(t)$ is a time varying constant term, and $u(t)$ is a white noise error term. Following standard practice for quarterly models, we set the lag length of $A_t(L)$ at six lags.

Combining $c(t)$ and $A_t(L)$ into a common coefficient matrix $B(t)$, we assumed that a typical row $b(t)$ of $B(t)$, i.e., the coefficients of a typical equation in model (1), followed a random walk specification

$$(2) \qquad b(t) = b(t-1) + e(t)$$

where $e(t)$ is a white noise term assumed independent of $u(t)$. For a given prior mean value of $b(t)$, $b(-1)$, a known initial covariance matrix of $b(t)$, $\sum(-1)$, a known covariance matrix W of the coefficient shocks $e(t)$, and a known value of the variance of each component of $u(t)$, the Kalman filter allows for recursive calculation of the linear projection of the coefficient vector $b(t)$ on information available at time t. Since estimation of the second moment matrices and the initial mean values needed for Kalman filtering would be computationally practical, an essential part of Sims's forecasting methodology involves the use of heuristic techniques that yield some informed guesses as to the value of these moments.

Our methods for choosing these moments closely followed those suggested in DLS, although we adopted some simplifications. Our specification for the prior means $b(-1)$ followed DLS by initially setting the coefficient of the first own lag equal to one, and all other coefficients equal to zero. Before specifying the second moments of the model, we then conducted a specification search over a fixed coefficient version of the model. With fixed coefficients, the covariance matrix W of the coefficient shocks $e(t)$ is constrained to equal zero, and the variance of the model error term $u(t)$ drops out of the Kalman filter calculations.[5/] For the coefficients of the kth lag of variable j in equation i, we assumed a prior standard error of the form

$$S(i,j,k) = g \cdot f(i,j)s(j)/[s(i) \cdot k] \tag{3}$$

where g is a parameter reflecting the overall "tightness" of the prior covariance matrix, $f(i,j)$ is a weight chosen to reflect the importance of variable j in explaining variable i, and $s(i)$ is the standard error of a univariate autoregression of variable i. We initially chose values of $g = .2$, $f(i,i) = 1$, and $f(i,j) = .3$ for j not equal to i. The initial covariance matrices $\Sigma(-1)$ were then taken as diagonal matrices with the squared values of $S(i,j)$ along their diagonals.[6/]

The forecasting performance of this model was then evaluated by examining its out-of-sample forecasting performance over the period 1965:4 through 1983:1 at one through 12 step ahead forecast horizons. Evaluation of out-of-sample forecasting performance utilized the summary measures proposed by DLS, i.e., at forecast horizon k we considered the measure

$$(4) \qquad J_k = \log \{\det \sum_t \nu_k(t)\nu_k(t)'\}$$

where $\nu_k(t)$ represents the error of a k-step ahead forecast made at time t. After an informal grid search, some small adjustments were made to the weights $f(i,j)$, which resulted in increased forecast accuracy at all horizons. These adjustments, along with other details of our specification search, are listed in Appendix B.

We then considered a random coefficient version of our model. For this model, we adopted the same prior means $b(-1)$ as with the fixed coefficient model. We took the variances of the error terms $u(t)$ as the estimated error variances from the fixed coefficient model, as of 1965:4. To specify the initial parameter covariance matrices $\sum(-1)$, we began by taking these to be equal to the estimated covariance matrices as of 1965:4 for the fixed coefficient model described above. We then made a number of adjustments to these matrices. The first adjustment consisted of specifying prior first and second moments for the sums of coefficients on lags of the same variable. Again following DLS, the prior mean for the sum of coefficients on own lags was set equal to one, and on lags of other variables equal to zero, with the net effect of shrinking the matrices $\Sigma(-1)$ towards zero. The second moments for the sums were set by scaling the prior variances of the summed coefficients. Here our procedure differed somewhat from DLS, in that we used two scaling factors π_1 and π_2.[7/] The factor π_1 was used as a scale factor for sums of coefficients in the equations for real GNP, the monetary base-to-debt ratio, and the deficit-to-GNP ratio, while the factor π_2 was applied to sums of the inflation rate, the T-bill rate, and the value of the dollar. In subsequent searches over the values of π_1 and π_2, we found that strong priors on sums were useful in improving the forecasting performance of the model for the first set of variables, while the opposite seemed true for the second set of variables. Given that the first set of variables are real quantities and the second nominal, this result is in approximate correspondence with an intuitive notion of "superneutrality."

Our second modification consisted of multiplying the $\Sigma(-1)$ matrices by a scaling factor π_3 which was also varied so as to maximize out-of-sample forecasting performance. The covariance matrices W of the coefficient shocks were then set by scaling the modified $\Sigma(-1)$ matrices by a scaling factor π_4.

Our final modification of the initial covariance matrices was not used by DLS, but nonetheless proved useful in increasing the forecast accuracy of the model.[8/] In this modification, an additional pseudo-observation was constructed for each series by forecasting the model out one period from the initial conditions. This pseudo-observation together with the initial conditions was then weighted by a scaling factor π_5, and the Kalman filter was used to update the coefficient estimates and the initial covariance matrices $\sum(-1)$. Since the forecast error for this pseudo-observation is by construction equal to zero, the Kalman filter does not alter the prior means of the coefficients. The effect on the initial covariance matrices is again to shrink them towards zero, amounting to a slight tightening of these initial second moments around the "random walk" prior for the mean of the coefficients.

We then conducted an informal search over the scaling factors π_1 through π_5, using the out-of-sample forecast error criteria J_k defined above. After some experimentation, we settled on the values

$$\pi_1 = 1000.0$$

$$\pi_2 = 1.0$$

$$\pi_3 = 1.7$$

$$\pi_4 = .000001$$

$$\pi_5 = 1.0$$

(A complete description of the random coefficient model specification and of the prior variances is given in Appendix C.)

C. <u>Out-of-Sample Forecasts</u>

The forecasting performance of the model is summarized in Table 1. Also given in Table 1 are forecast performance statistics for the fixed coefficient VAR model described above, as well as for a benchmark system of AR(4) fixed coefficient univariate models, which were estimated by simple least squares.

As can be seen from Table 1, the DLS methodology was generally successful in delivering a forecasting model with desirable out-of-sample forecasting properties. Although the fixed coefficient VAR was able to generate significant improvements over the benchmark forecasts at shorter horizons, its performance deteriorated over longer horizons. The greater flexibility of the DLS-type specification then resulted in large improvements in the fixed coefficient model at longer horizons, as well as some smaller gains over the short term. In addition, the DLS approach was generally able to outperform a random walk forecast at all but the longest horizons, as evidenced by the Theil U-statistics reported below.

II. Structural Instability Following Policy Changes

A. Evidence of Policy Changes

It seems clear that monetary policy changed in the fall of 1979, when the Federal Reserve began following a new operating procedure. And it seems clear that budget policy changed in the fall of 1981, when the first Reagan budget was implemented. What is not clear, however, is whether either policy change would be considered large in a statistical sense or whether either change would be better characterized as a shift in a policy rule or as a random disturbance under a given policy rule. In this section we informally examine the behavior of the monetary and budget policy indicators before and after the respective policy changes in order to address these issues.

Simple plots of the monetary and fiscal policy indicators reveal somewhat unusual behavior at the times of the corresponding policy changes (see figures 1a and 1b). In 1979 our monetary policy indicator, the ratio of the monetary base to total outside federal debt, turned up sharply after several years of substantial decline. In 1981 our fiscal policy indicator, the ratio of the deficit net-of-interest to GNP, began a sustained climb from around 0 to a range of 2-4 percent. While the plots of the policy indicators prove nothing, they at least suggest that the changes in policy may have been significant, and they provide reason to look at some additional measures of policy change.

We look at three additional measures: one-step-ahead forecast errors of the policy indicators, estimates of the coefficients on the first own lag in the policy indicator equations, and comparisons to the actual outcomes of unconditional dynamic forecasts of the policy indicators from the times the policy changes took place. The first two measures provide no evidence of policy change, but the third one does. Together the measures suggest that the changes in policy, if any occurred, were cumulative and affected more than the first-order properties of the indicators. The third measure suggests that the policy changes may have been significant and may be better characterized as rule changes since there is no tendency for the forecasts to converge to the actual outcomes.

One-step-ahead forecast errors do not seem to be larger or have different serial correlation properties following the policy changes (see figures 2a and 2b). Simply by eyeballing these charts one is led to believe that the policy changes in 1979 and 1981 were not significant.

The coefficients on the own first lag similarly do not seem to move unusually after the policy change (see figures 3 and 4). The coefficient on the own first lag in the deficit/GNP equation, however, does flatten out some and then gradually rise after 1981.

Dynamic forecasts of the policy indicators made at the time of the corresponding policy changes reveal large and persistent errors (see figures 5 and 6). The size of the errors suggests that the policy changes may have been significant, and their persistence suggests they may have been in the nature of rule changes.

In summary, anecdotal evidence, simple plots, and dynamic forecasts suggest that there may have been significant changes in the monetary policy rule in 1979 and in the fiscal policy rule in 1981. The evidence is far from conclusive, however. One-step-ahead forecast errors and estimates of coefficients on first own lags show little in the way of unusual patterns following the policy changes.

B. Evidence of Coefficient Instability

If the changes in policies in 1979 and 1981 were significant changes in rules, then the Lucas critique implies that we should find evidence of coefficient instability in the nonpolicy equations following the changes. Because our method of model construction does not permit us to formally test for structural instability, we examine a number of different measures of coefficient changes.

We begin by examining one-step-ahead forecast errors (see figures 7a-7d). If there were significant changes in coefficients, we would expect to find some large errors. However, if we find large errors, they could just be the result of large residuals. So this evidence is of the necessary, but not sufficient, variety. The errors for real GNP do not seem extraordinary following either policy change. The errors for inflation seem large only after the monetary policy change, and they seem to show that the model over-corrected for misses at that time. The errors for the three-month T-bill rate seem unusual following both policy changes. After the monetary policy change, the errors became quite large, frequently exceeding two standard errors of forecast. After the fiscal policy change, the errors no longer seemed random about zero but, instead, seemed to trend upward. Finally, the errors for the dollar seem to show that, perhaps, beginning in 1980 the equation for the dollar went more and more off the mark. The figures as a whole seem to indicate that if we find evidence of coefficient instability, it will be with respect to the financial variables: the interest rate and the dollar.

We next examine the estimates of the coefficients on the first own lags (see figures 8a-8h). The estimate for the coefficient on real GNP seemed to settle down in about 1975, and it showed few signs of instability following the policy changes. The estimate for the coefficient on inflation also did not show much instability following the policy changes, although changes in the estimate seemed to follow a lower order process after 1979. In contrast to the coefficients on real GNP and inflation, the estimate of the coefficient on the first own lag in the T-bill equation shows spectacular signs of instability following the policy changes. The revision in the estimate following the monetary policy change is the largest and sharpest. It suggests that any model with time-varying coefficients that adjust smoothly would not predict well the effects of the monetary policy change on the interest rate. The estimate of the coefficient on the dollar also shows signs of instability, but most of the instability doesn't occur until 1985, well after both policy changes.

In order to check for changes in other coefficients we examine some measures which are functions of all the coefficients. We examine forecasts made at the time of the policy changes and decompositions of variance before and after policy changes.

We consider two forecasts for each policy change and compare them to the actual outcomes. We look at unconditional forecasts and forecasts with coefficient estimates conditioned on data up to the policy change, but with the relevant policy variable set at its actual future values. The conditional forecasts are the most likely outcomes according to our model, given the initial coefficient estimates, the future path of the relevant policy variable, and the assumption of no future parameter change (see figures 9a-9e and 10a-10e).[9] If the policy changes were important, we would expect to see large differences between unconditional forecasts and the actual outcomes, which we do especially for the interest rate and the dollar. If the policy changes were like drawings of residuals which implied no instability in coefficients, we would expect the conditional forecasts to largely close the gaps between the unconditional forecasts and the actual outcomes. The conditional forecasts in fact close very little of the gaps. These graphs suggest that forecast errors following the policy changes tended to be large, and they would still have been large if the actual future values of the relevant policy variable were known at the times of the policy changes.

Lastly, to examine changes in the structure of the model following the policy changes we constructed a series of forecast error decompositions based on the model's estimated coefficients and the empirically generated variance-covariance matrix V of one-step ahead forecast errors. These decompositions were constructed for the dates 1979:3, 1980:3, 1981:4, and 1982:4. These decompositions differ from those usually reported for VAR models in two respects. First, although these decompositions are generated from a model with time-varying coefficients, they are generated by holding the model coefficients constant at the their current values. Thus these error decompositions are probably best taken as rough approximations of the true decompositions, given the time variation we are allowing in the coefficients.[10] A second difference is the method by which we orthogonalize the model shocks.[11] The most common method of orthogonalization is to assume a Wold causal chain model or "ordering" for the shocks, corresponding to a LL' factorization of the forecast error covariance matrix V (see Sims [1980a,1980b]). A second method is to construct a Cowles-Commission-type model for the shocks (see Blanchard and Watson [1984], Sims [1985], or Bernanke [forthcoming]). We used a third method, taking the orthogonalized shocks as the principal components of one-step-ahead forecast errors, which corresponds to an eigenvector factorization of V.

Our orthogonalization method has the advantage of being somewhat less arbitrary than the other two methods. A corresponding disadvantage is that the resulting decompositions can be difficult to interpret. Because the eigenvector factorization depends on the scale of the forecast errors, we first normalized by dividing the model forecast errors by their sample standard deviations and correspondingly rescaling the model coefficients. Forecast error decompositions were then calculated for the six principal components based on the eigenvector decomposition of the variance-covariance matrix of the normalized forecast errors. These decompositions are reported in Tables 2-5.

Tables 2-5 highlight some of the interesting properties of our reduced form forecasting model. Especially noticeable is the overriding importance of the first component in explaining movements in real GNP, inflation, and and the value of the dollar, which is suggestive of the dynamics of real business cycle models.[12] The second component is important in explaining short-term movements in the policy variables, and the third component is important for explaining forecast errors in interest rates.

The variance decompositions reported in these tables also reveal important shifts in these decompositions over time. From 1979:3 to 1980:3, for example, the most noticeable differences are the increase in the importance of the third component in explaining the forecast error for the T-bill rate, the increase in the importance of the first component for the base/debt ratio, and the increase in the importance of the second component for the deficit/GNP ratio. By the fourth quarter of 1981, the decomposition for the T-bill rate seems to have drifted back to its 1979:3 pattern, while the shifts for the policy variables seem to remain in place. From 1981:4 to 1982:4, the shifts tend to be relatively smaller, implying a less fundamental change in the model's dynamics over this time period.

III. The General Accuracy of Conditional Forecasting

The mixed results obtained for the DLS conditional forecasting methodology for the two policy changes we considered, led us to examine the efficacy of the methodology over arbitrary periods. The natural question to ask seemed to be the following one. Supposing that a forecaster had access to future values of one or both policy variables of our VAR model, would access to this information have allowed this forecaster to improve the out-of-sample forecasting record for the other variables in the model?

We attempted to answer this question by simulating the out-of-sample forecasting performance of the DLS conditional forecasting procedure over the period 1965:4 through 1983:1 at horizons of one to 12 quarters ahead.[13/] In these simulations, we conditioned our forecasts on the next 12 quarters of the monetary and fiscal policy variables, both singly and together. Our measure of forecast accuracy was the log determinant of the covariance matrix of out-of-sample forecast errors for the nonpolicy variables of the model, i.e., of log real GNP, inflation, the T-bill rate, and the dollar. The initial results of this exercise, reported in Table 6, are not favorable to the DLS conditional forecasting procedure.

Table 6 indicates that for the period 1965:4-1983:1, conditioning on the next twelve quarters of the base/debt ratio would have generally led to a deterioration in the forecasts of the nonpolicy variables of the model. Further, conditioning on the deficit/GNP ratio would have led to only slight increases in forecast accuracy. Using both policy variables would have again generally detracted from forecast accuracy.

After viewing the results for the period 1965:4-1983:1, we suspected that the poor performance of the conditional forecasting procedure over this period might have resulted from the small sample sizes available for forecasting at the beginning of this period. We then decided to conduct a second set of comparisons based on performance only over the last ten years. In this set of comparisons, the forecast horizon was cut in half to six quarters to conserve degrees of freedom, and conditional forecasts were also conditioned on actual values of policy variables over the next six quarters. The results of this exercise, also included in Table 6, are more favorable to the DLS procedure. Except at the one quarter horizon, adding information about future values of policy variables appears to increase forecast accuracy. Moreover, examination of forecast error covariance matrices (not reported here) indicated the forecast error variances were reduced for each of the nonpolicy variables at almost all horizons.

While these improvements in forecast accuracy are large enough to suggest that the DLS conditional forecasting technique may be of some practical utility to forecasters, they are nonetheless disappointingly small, being under 5 percent in all cases. Given the discussion of the Introduction, the important question would then seem to be how much of the remaining forecast error can be explained by predictable changes in the model coefficients. Ideally, the answer to this question would involve simulation of the true conditional forecasts of the model, as opposed to the simulations reported in Table 6, which assume no parameter change in the future. Unfortunately these true conditional forecasts are, in general, quite difficult and expensive to compute. As an alternative, we considered a very simple procedure which attempts to account for parameter variation in a somewhat ad hoc way. This procedure consisted of doing a sequence of one quarter ahead forecasts, conditional on policy variables, and sequentially applying the Kalman filter to the model coefficients, using the previous quarter's conditional forecast. This naive procedure would be a reasonable one if the forecast horizon and the conditioning information were only one period ahead, but is suspect at longer horizons, for essentially two reasons. The first is that even for a VAR with known, fixed coefficients, a sequence of one period ahead conditional forecasts doesn't correspond to a true multi-period conditional forecast, unless the variable(s) being conditioned on are exogenous. The second reason is that sequential applications of the Kalman filter also fail to take into account the information contained in future values of policy variables for current coefficient estimates.

We also computed a second set of sequential one quarter ahead forecasts conditional on policy variables. In this set of forecasts, we again applied the Kalman filter after each step, only this time we used the actual data for all variables to update the model coefficients. This is another way of saying that we used the historical coefficients of the model to construct a sequence of one step ahead conditional forecasts. Although this is also clearly an ad hoc procedure with many problems of interpretation, we used these forecasts to get some rough measure of how well a forecaster might do if, in addition to the future values of some policy variables, the future values of shocks to the model coefficients were known with perfect accuracy.

Table 7 compares the results of simulating the two naive procedures described above over the last ten years of data, together with the results of unconditional and conditional procedures reported on in Table 6. As in Table 6, the forecasts are "conditioned" on six future quarters of data on both the base/debt and deficit/GNP ratio. The first two columns of Table 7 are reproduced from Table 6. The third column of Table 7 reveals that the for our VAR model, the naive sequential forecasting procedure generally performs only slightly better out-of-sample than the DLS procedure. However, the fact that it does not perform worse than the DLS procedure suggests that further gains in forecasting accuracy might be possible if more sophisticated procedures were used to account for the influence of future policy variables on parameter values. That message is reinforced by the last column of Table 7, which unequivocally points to coefficient variation as an important source of error in conditional forecasting. Of course, if the random walk parameter specification of equation (2) is approximately correct, then this variation would be unforecastable in an unconditional sense. However, the potential for improvement in conditional forecasting due to improved forecasts of coefficient changes remains largely unexplored.

5. Summary and Conclusion

In this paper we have considered the historical accuracy of Sims's methodology for policy evaluation. We have done this by fitting an unconstrained VAR model to a small number of macroeconomic time series, and then using this model to simulate the historical performance of the conditional forecasting technique described in Doan, Litterman, and Sims [1984]. Our simulations suggest that over the last ten years, conditioning on the actual future paths of policy variables would have in fact led to improvements in the accuracy of postsample forecasts for nonpolicy variables. The magnitude of these improvements is small, however, typically being less than 5 percent. Also, consideration of historical episodes associated with policy changes suggest that the performance of the DLS conditional forecasting technique is not particularly strong over such episodes. Our feeling is that this weakness reflects the fact that the DLS conditional forecasting technique ignores potential future variation in the model coefficients, which can be quite large during such policy change episodes.

Our overall conclusion is that the Lucas critique is valid in an empirical sense, and that its quantitative significance cannot be successfully dealt with using the DLS conditional forecasting methodology. Given the exploratory nature of our analysis, however, we do not wish to rule out the possibility that the effects of policy may be accurately predicted using purely statistical methods. Still, our results suggest that some modifications of the currently available techniques are in order before such methods can reliably be used for policy analysis.

Footnotes

1/See, for example, Lucas [1976].

2/See Sims [1982, p. 120] and Sims [1986, p. 7].

3/Sims [1982, pp. 138-139].

4/The role of time variation in the model parameters is potentially ambiguous in Sims's methodology. Although the introduction of the device of time variation in an article on policy evaluation (i.e., Sims [1982]) seems to suggest that this variation is associated with the effects of policy change, Sims never explicitly says this. In any event, the time variation feature per se is not really crucial to the analysis of DLS or of this paper, since in both cases the amount of time variation allowed for is quite small. All of the calculations reported below would have yielded similar results had they been performed for fixed coefficient models. Nonetheless, we have followed Sims's lead in using the time-varying parameter feature because of its more desirable forecasting properties.

5/It is well known that for this case, "Bayesian vector autoregression" essentially corresponds to a recursive, equation-by-equation implementation of Theil's mixed estimation procedure. In this sense, our specification of first and second moments described above amounts to the addition of pseudo-observations to the relatively short economic time series used for this study.

6/Except for the element of $\sum(-1)$ corresponding to the constant term, which was left free, corresponding to a diffuse prior.

7/The term "hyperparameter" is used by DLS for such factors such as π_1 and π_2, which parameterize the initial first and second moments of the model coefficients.

8/The authors are grateful to Chris Sims for suggesting this modification.

9/All conditional forecasts in this paper are generated using the sample variance-covariance matrix of forecast errors V. Although DLS (p. 69) suggest that using this matrix may lead to instability in the model's conditional forecasts, they do not point to any clearly superior alternative to this procedure.

10/A more thorough defense of this approximation is given in DLS.

11/For forecasting purposes, which orthogonalization is adopted is innocuous in the sense that unless some additional side conditions are imposed, the conditional forecasts of the model are independent of the orthogonalization.

12/Although this suggestion requires some leap of faith, it is reinforced by the fact that, over the time periods covered by Tables 2-5, responses of GNP and inflation to an impulse in the first component were always of the opposite sign for at least 10 quarters. For a useful discussion of the econometric implications of real business cycle models, see Altug [1986].

13/Some care is needed in interpreting the term "out-of-sample" here, since these forecasts take into account data revisions announced after the forecast date, as well as hyperparameter settings that utilize subsequent data. Hence the postsample forecasts described above are likely to be more accurate than real-time forecasts made over the same period.

Appendix A. Data Series

Series	Units	Source
Real GNP	Billions of 1982 dollars	U.S. Dept. of Commerce
GNP Deflator	Percent per annum (400 xΔ logs)	U.S. Dept. of Commerce
3-month T-bill Rate	Percent per annum (Quarterly Geometric Avg. of Monthly Series)	FRB
Trade-weighted Value of the Dollar	March 1973=100 (Quarterly Geometric Avg. of Monthly Series)	FRB
Base/Debt Ratio	(Ratio)	See below
Deficit/GNP Ratio	(Ratio)	See below

The ratio series were constructed as follows: Deficit/GNP was taken as the ratio of the Federal deficit (N.I.P.A. basis, s.a.a.r.) to nominal GNP. Denoting the deficit net-of-interest as NETDEF, this figure was calculated as

$$\text{(A.1)} \qquad NETDEF_t = (GEXPF_t - INTGF_t) - (TGF_t - FRBFIT_t)$$

where

GEXPF = Federal government total expenditures (N.I.P.A., s.a.a.r.)

INTGF = Interest payments on debt (N.I.P.A., s.a.a.r.)

TGF = Federal government receipts (N.I.P.A., s.a.a.r.)

FRBFIT = Federal Reserve profits (FRB, s.a.a.r. Before 1959, annual data are interpolated to quarterly.)

GEXPF-INTGF is then federal expenditures net-of-interest and TGF-FRBFIT is federal revenues net of Federal Reserve profits. Our measure NETDEF is sometimes referred to as the primary deficit.

Base/Debt was taken as the ratio of St. Louis Fed adjusted monetary base (s.a.) to total outside federal debt held by the public. The debt figure was calculated using a simple version of the government budget constraint:

$$\text{(A.2)} \qquad DEBT_t = DEBT_{t-1} + (GEXPF_t - TGF_t)/4 - \Delta MBASE_t$$

where

(GEXPF-TGF)/4 is the quarterly gross-of-interest deficit not at an annual rate.

The debt figure for 1947:4 was approximated by dividing net interest payments for that date by a weighted average of interest rates on various maturities of Federal debt. The weights were determined by the maturity profile of Federal debt in 1947, as reported in the Treasury Bulletin.

Appendix B. Priors Assumed for the Fixed Coefficients VAR Model

The model variables are numbered as log real GNP (1), inflation (2), T-bill rate (3), the value of the dollar (4), the base/debt ratio (5), and the deficit/GNP ratio (6). The initial specification of the prior standard error for the coefficients of the kth lag of variable j in equation i was of the form

$$S(i,j,k) = g \cdot f(i,j)s(j)/[s(i) \cdot k] \tag{3}$$

We initially chose values of $g = .2$, $f(i,i) = 1$, and $f(i,j) = .3$ for j not equal to i. After an informal search over the weights $f(i,j)$, using the postsample forecasting performance of the fixed weight VAR as our objective function, we revised the matrix of weights $F \equiv [f(i,j)]$ to the following:

$$F = \begin{bmatrix} 1.0 & 0.3 & 0.5 & 0.3 & 0.3 & 0.3 \\ 0.3 & 1.0 & 0.3 & 0.3 & 0.3 & 0.3 \\ 0.2 & 0.2 & 1.0 & 0.2 & 0.2 & 0.2 \\ 0.3 & 0.3 & 0.3 & 1.0 & 0.3 & 0.3 \\ 0.3 & 0.3 & 0.3 & 0.3 & 1.0 & 0.3 \\ 0.4 & 0.2 & 0.2 & 0.2 & 0.2 & 1.0 \end{bmatrix}$$

Appendix C. Specification of the Random Coefficient VAR Model and Prior Covariance Matrices

Summary of Model Specification

Write component i of equation (1) as

(C.1) $y_i(t$ ... $\sum^{6} \sum^{6}$ ... $+ u_i(t); \; u_i(t) \sim IIDN(0,\sigma_i^2)$.

Defining $b_i(t)$ ...

Will, ask Kathy R.
if she has this symbol
on a stencil. We do
not have it.

$b_i($ ...

we assumed th ...

(C.2) $b_i($ ... DR ... $,W_i)$,

and $e_i(t)$ u_i $\perp$ ..., $b_i(-1)$ was assumed to have mean given by

(C.3) $a_{ii1}(-1) = 1; \; a_{ij1}(-1) = 0$ otherwise; $c_i(-1) = 0$

and variance-covariance matrix $\sum_i(-1)$.

Specification of Prior Covariance Matrices

We initially constrained W_i to be zero, and estimated a fixed coefficient version of the model over 1948:2 - 1965:4, using priors described in Appendix B. Let $\bar{\sum}_i$ be 1965:4 estimate of the variance-covariance matrix of the coefficients in the i^{th} equation of the fixed-coefficient model.

Taking $\bar{\sum}_i$ as our initial guess for $\sum_i(-1)$ in the random coefficient model, priors on sums of coefficients are introduced by using dummy observations of the form

(C.4) $\quad S_{ij}\theta_{ij} = v_{ij}$

where $S_{ij} = \{\pi_1 s(j)/s(i)\}[1\ldots1]$ or $\{\pi_2 s(j)/s(i)\}[1\ldots1]$, θ_{ij} is the vector of coefficients on variable j in $b_i(-1)$, and v_{ij} is an error term assumed to have unit variance. Letting $\bar{\Sigma}_{ij}$ be the variance-covariance matrix of θ_{ij} implied by Σ_i, $\bar{\Sigma}_{ij}$ was then adjusted to yield

(C.5) $\quad \Sigma^*_{ij} = \bar{\Sigma}_{ij} - \{\bar{\Sigma}_{ij}S'_{ij}S_{ij}\bar{\Sigma}_{ij}/(1+S_{ij}\bar{\Sigma}_{ij}S'_{ij})\}$

(cf. DLS p. 14.) The resulting guess for $\Sigma_i(-1)$, Σ^{**}_i, is now scaled to yield

(C.6) $\quad \Sigma^+_i = \pi_3\, \Sigma^{**}_i.$

We then specify the matrix W as

(C.7) $\quad W = \pi_4\, \Sigma^+_i.$

Our final modification for our guess at the value of $\Sigma_i(-1)$ is implemented by introducing a pseudo-observation $y^*_i(0) = \pi_5 y_i(-1)$, where $y_i(-1)$ is the value of series i in 1949:3. Our final guess for $\Sigma_i(-1)$ is then given by the familiar Kalman filtering formula

(C.8) $\quad \hat{\Sigma}_i(-1) = \Sigma^+_i - \Sigma^+_i X(-1)'\ [X(-1)\Sigma^+_i X(-1)' + \hat{\sigma}^2_i]^{-1} X(-1)\ \Sigma^+_i + W_i$

where $\quad X(-1) = \pi_5[1\ y(-1)'\ y(-2)'\ldots y(-6)']'$

and $\hat{\sigma}^2_i$ is the estimate of $\sigma_i{}^2$ from the fixed coefficient VAR. In practice, the Kalman filtering algorithm used in RATS also attempts to update the model coefficients while implementing modification (C.8). Updating of coefficients is avoided by scaling $y^*(0)$ by Π_5, implying a perfect initial forecast given a random walk prior mean and initial conditions $X(-1)$.

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Table 1

Out-of-Sample Forecasting Performance

Theil U-Statistics*

Variable	Univariate Model	Fixed Coefficient VAR	Random Coefficient VAR
1-Step Horizon			
Log Real GNP	0.89037084	0.87535508	0.84075752
Inflation	1.1205214	0.86674778	0.89516270
T-bill Rate	1.0117206	0.99490968	0.98428203
Dollar	1.0492159	1.0060888	0.99792794
Base/Debt	0.69227165	0.66456204	0.66343662
Deficit/GNP	1.0958964	1.0204268	0.98709295
Log Determinant**	-26.38745770	-27.59246344	-27.74651049
Average Improvement***		(10.0%)	(1.3%)
4-Step Horizon			
Log Real GNP	0.78939078	0.83602656	0.72352885
Inflation	1.2362319	0.75290589	0.81015648
T-bill Rate	1.1097015	0.95967090	0.93763422
Dollar	1.0249468	0.98931803	0.96217418
Base/Debt	0.97035277	0.85103865	0.82525172
Deficit/GNP	1.0816631	0.96755082	0.89142564
Log Determinant	-16.40680706	-17.96894740	-19.09395578
Average Improvement		(13.0%)	(9.4%)
8-Step Horizon			
Log Real GNP	0.70038278	0.88319848	0.63079529
Inflation	1.1966208	0.85603576	0.86030707
T-bill Rate	1.1016185	0.90079367	0.88894499
Dollar	1.0289541	1.0013363	0.99364748
Base/Debt	1.1663969	1.1096891	0.99779621
Deficit/GNP	0.97506862	0.93170607	0.80428217
Log Determinant	-12.22140537	-12.84476399	-15.11565128
Average Improvement		(5.2%)	(18.9%)

(continued)

(Table 1 continued)

Variable	Univariate Model	Fixed Coefficient VAR	Random Coefficient VAR
12-Step Horizon			
Log Real GNP	0.60144292	0.96946851	0.49536047
Inflation	1.2067822	0.99337068	0.89866873
T-bill Rate	1.1449781	0.84518427	0.85586603
Dollar	1.0655788	1.0676973	1.0685242
Base/Debt	1.3173133	1.3679806	1.0656031
Deficit/GNP	0.92204479	0.85905479	0.73974739
Log Determinant	-10.24498619	-10.26939518	-13.38444321
Averaga Improvement		(0.2%)	(26.0%)

*Ratio of RMS forecast error to RMS forecast error of a forecast of no change.

**Value of J.

***Approximate average percentage reduction in standard error of the forecast obtained by taking the difference in log determinants and multiplying by 8.33 (divide by 12 to get standard errors for 6 variables and multiply by 100 to get percent). The first improvement is of the VAR over the univariate model; the second is of the random coefficient VAR over the fixed coefficient VAR.

Table 2

Forecast Error Decomposition

Implied by Model Estimates As of 1979:3

Principal Components of Forecast Errors

Weight on Shock to:

Component	Real GNP	Inflation	T-bill	Dollar	Base/Debt	Def./GNP
P1	4.42	2.21	2.34	3.64	6.14	-5.82
P2	-3.72	-3.10	4.77	-2.60	1.23	-2.42
P3	-1.43	6.02	1.08	-3.28	1.03	.67
P4	-.94	1.46	4.24	4.36	-1.91	2.25
P5	4.43	-.67	2.58	-2.51	-1.36	1.13
P6	-.01	-.82	.11	.00	2.86	2.75

		Percentage of Forecast Error Variance Due to					
Step	Standard Error*	P1	P2	P3	P4	P5	P6
Decomposition of Variance for Log Real GNP							
1	1.562	84.697	1.768	0.431	0.012	12.734	0.355
4	3.472	79.713	1.089	2.146	0.071	15.931	1.049
8	6.227	77.039	2.041	9.205	0.222	8.075	3.416
12	10.77	85.915	3.509	4.468	0.361	2.770	2.975
16	14.81	87.906	4.612	2.464	0.633	1.600	2.782
Decomposition of Variance for Inflation							
1	1.807	86.752	7.063	0.005	1.566	3.959	0.652
4	2.847	85.841	8.261	0.023	1.234	4.006	0.633
8	3.165	85.240	8.687	0.164	1.184	4.145	0.577
12	3.235	84.030	8.458	0.311	2.408	4.155	0.636
16	3.285	82.172	8.282	0.382	4.256	4.044	0.861

(continued)

(Table 2 continued)

Step	Standard Error*	Percentage of Forecast Error Variance Due to P1	P2	P3	P4	P5	P6
Decomposition of Variance for T-bills							
1	0.9933	0.610	7.466	79.751	8.999	2.516	0.654
4	1.798	2.413	13.701	75.599	6.176	1.754	0.355
8	2.100	3.011	12.621	64.557	11.358	6.437	2.013
12	2.698	11.107	19.341	44.144	13.669	5.140	6.596
16	3.721	36.709	20.826	25.164	8.397	3.351	5.551
Decomposition of Variance for the Dollar							
1	1.297	63.631	10.444	8.670	13.081	1.920	2.251
4	2.599	64.027	8.150	7.122	16.964	2.187	1.548
8	3.387	61.176	7.046	5.514	21.939	2.843	1.479
12	3.877	56.272	8.320	4.428	25.853	2.963	2.162
16	4.113	50.608	10.005	4.083	29.804	2.699	2.799
Decomposition of Variance for the Base/Debt Ratio							
1	1.022	13.503	55.501	4.815	18.944	0.540	6.695
4	3.805	28.638	47.794	8.113	11.700	0.111	3.641
8	6.210	34.526	33.190	10.176	19.474	0.104	2.528
12	10.27	62.125	12.575	4.072	17.233	0.676	3.316
16	16.93	78.561	5.298	1.502	10.004	1.975	2.656
Decomposition of Variance for Deficit/GNP Ratio							
1	1.062	5.577	75.241	7.400	0.273	1.337	10.169
4	1.704	5.105	67.465	3.221	1.665	0.968	21.573
8	2.281	15.775	52.527	3.521	5.046	3.146	19.982
12	3.428	46.023	33.202	1.642	4.636	4.452	10.043
16	3.652	48.575	32.154	1.490	4.208	4.700	8.869

*Ratio of theoretical RMS of forecast error, assuming no coefficient uncertainty, to the sample standard deviation of one-step-ahead forecast errors for that variable. Ratios for one-step-ahead errors may exceed one due to the empirical bias of the model's postsample forecasts.

Table 3

Forecast Error Decomposition

Implied by Model Estimates as of 1980:3

Principal Components of Forecast Errors

Weight on Shock to:

Component	Real GNP	Inflation	T-bill	Dollar	Base/Debt	Def./GNP
P1	4.63	2.01	3.17	3.28	6.38	-6.17
P2	2.98	3.88	-4.16	4.20	-1.05	2.50
P3	-1.24	5.80	-.17	-4.33	1.47	.09
P4	-.71	2.08	5.40	2.19	-1.89	2.13
P5	5.26	-.71	1.18	-2.99	-1.53	1.15
P6	.04	-.79	.22	-.05	2.87	2.83

		Percentage of Forecast Error Variance Due to					
Step	Standard Error*	P1	P2	P3	P4	P5	P6
Decomposition of Variance for Log Real GNP							
1	1.581	83.751	0.341	3.138	10.746	1.846	0.173
4	3.557	80.277	0.407	1.880	14.452	2.427	0.553
8	6.440	78.213	1.515	7.987	7.882	1.601	2.799
12	11.15	86.881	3.107	4.374	2.697	0.588	2.350
16	15.32	89.077	4.201	2.556	1.648	0.375	2.140
Decomposition of Variance for Inflation							
1	1.868	86.695	7.816	0.117	4.722	0.003	0.646
4	2.945	85.724	8.926	0.287	4.395	0.040	0.625
8	3.288	85.236	9.159	0.480	3.974	0.585	0.564
12	3.366	84.303	8.855	0.547	3.832	1.829	0.631
16	3.408	82.803	8.726	0.536	4.101	2.975	0.856

(continued)

(Table 3 continued)

Step	Standard Error*	Percentage of Forecast Error Variance Due to P1	P2	P3	P4	P5	P6
Decomposition of Variance for T-bills							
1	0.9917	0.043	1.305	87.547	1.009	9.972	0.122
4	1.502	0.113	4.626	86.657	0.668	7.797	0.136
8	1.849	6.937	4.615	71.381	1.154	14.133	1.777
12	2.251	8.696	15.200	53.174	0.972	15.332	6.625
16	2.905	27.187	21.163	34.997	0.968	9.564	6.118
Decomposition of Variance for the Dollar							
1	1.338	68.906	10.245	6.811	0.448	11.598	1.988
4	2.662	69.537	8.430	5.068	0.567	14.878	1.517
8	3.443	67.643	7.453	3.873	0.552	18.948	1.528
12	3.932	64.111	8.442	3.035	0.604	21.653	2.152
16	4.135	59.454	9.990	2.747	1.106	23.967	2.732
Decomposition of Variance for the Base/Debt Ratio							
1	1.046	23.172	49.632	3.627	8.145	10.167	5.254
4	3.748	35.338	43.134	5.270	4.506	8.060	3.688
8	5.766	37.652	32.143	6.831	4.623	16.048	2.700
12	9.659	66.282	11.867	2.726	5.106	10.805	3.210
16	16.39	82.431	4.513	1.358	5.020	4.407	2.268
Decomposition of Variance for Deficit/GNP Ratio							
1	1.025	0.518	84.792	2.787	0.477	0.093	11.330
4	1.601	2.743	72.133	2.528	1.457	1.269	19.866
8	2.184	17.165	54.424	2.598	4.999	1.599	19.212
12	3.309	47.860	33.601	1.633	6.420	0.817	9.666
16	3.536	50.523	32.248	1.515	6.441	0.777	8.492

*Ratio of theoretical RMS of forecast error, assuming no coefficient uncertainty, to the sample standard deviation of one-step-ahead forecast errors for that variable. Ratios for one-step-ahead errors may exceed one due to the empirical bias of the model's postsample forecasts.

Table 4

Forecast Error Decomposition

Implied by Model Estimates As of 1981:4

Principal Components of Forecast Errors

Weight on Shock to:

Component	Real GNP	Inflation	T-bill	Dollar	Base/Debt	Def./GNP
P1	4.21	1.75	4.17	4.28	6.56	-6.28
P2	3.18	5.58	-4.72	-2.49	.97	-.13
P3	1.77	3.00	1.39	5.11	-2.65	3.66
P4	5.52	-4.32	-1.84	.33	-1.29	.16
P5	2.15	.88	4.28	-3.71	-.62	1.34
P6	.00	-.72	-.29	.03	3.19	2.96

Step	Standard Error*	Percentage of Forecast Error Variance Due to P1	P2	P3	P4	P5	P6
Decomposition of Variance for Log Real GNP							
1	1.486	73.950	0.331	13.978	4.689	7.034	0.016
4	3.392	71.606	0.621	6.188	12.952	8.559	0.072
8	6.824	79.006	1.402	4.870	9.951	3.752	1.017
12	12.08	89.030	1.757	3.580	3.536	1.240	0.854
16	16.39	90.983	2.497	2.986	1.924	0.707	0.900
Decomposition of Variance for Inflation							
1	1.883	86.923	6.253	2.739	3.114	0.209	0.760
4	2.955	86.333	7.187	2.624	2.617	0.478	0.759
8	3.275	85.810	7.549	2.309	2.231	1.375	0.724
12	3.337	84.059	7.485	2.717	2.375	2.655	0.706
16	3.466	81.998	6.972	4.250	2.740	3.334	0.702

(continued)

(Table 4 continued)

Step	Standard Error*	Percentage of Forecast Error Variance Due to P1	P2	P3	P4	P5	P6
Decomposition of Variance for T-bills							
1	1.005	3.494	0.201	79.580	7.399	8.489	0.834
4	1.727	11.397	0.119	72.596	8.454	6.733	0.698
8	2.219	29.104	3.678	51.167	5.880	8.247	1.921
12	2.422	26.660	10.853	44.080	4.975	9.960	3.468
16	2.783	29.457	17.660	37.215	3.875	8.291	3.500
Decomposition of Variance for the Dollar							
1	1.352	71.569	9.908	0.026	6.116	11.237	1.142
4	2.512	68.128	7.765	1.485	6.355	15.618	0.645
8	2.975	59.398	6.188	5.684	6.625	21.637	0.465
12	3.358	48.267	5.150	15.909	5.759	24.519	0.393
16	3.977	48.234	3.760	23.291	4.679	19.751	0.281
Decomposition of Variance for the Base/Debt Ratio							
1	1.078	29.067	45.233	0.267	17.601	3.091	4.738
4	3.486	30.090	42.222	1.407	15.988	6.742	3.548
8	5.294	28.784	28.584	1.449	18.754	19.850	2.576
12	10.21	67.308	8.049	4.533	8.729	9.289	2.089
16	18.00	82.864	2.697	4.856	4.846	3.289	1.445
Decomposition of Variance for Deficit/GNP Ratio							
1	1.006	0.038	87.689	0.896	0.219	0.139	11.016
4	1.552	1.216	69.307	7.029	0.531	1.365	20.549
8	2.237	20.192	46.863	7.132	5.059	2.668	18.082
12	3.643	56.640	23.241	6.228	4.835	1.201	7.851
16	3.896	58.624	22.520	5.992	4.742	1.203	6.916

*Ratio of theoretical RMS of forecast error, assuming no coefficient uncertainty, to the sample standard deviation of one-step-ahead forecast errors for that variable. Ratios for one-step-ahead errors may exceed one due to the empirical bias of the model's postsample forecasts.

Table 5

Forecast Error Decomposition

Implied by Model Estimates As of 1982:4

Principal Components of Forecast Errors

Weight on Shock to:

Component	Real GNP	Inflation	T-bill	Dollar	Base/Debt	Def./GNP
P1	4.50	1.87	4.31	4.49	6.72	-6.44
P2	2.22	5.77	-4.83	-3.15	1.53	-.60
P3	2.05	3.95	1.38	4.53	-2.66	3.89
P4	6.11	-3.61	-1.86	-.20	-1.38	.39
P5	1.66	1.04	4.45	-4.18	-.47	1.03
P6	.03	-.74	-.21	-.01	3.24	3.04

		Percentage of Forecast Error Variance Due to					
Step	Standard Error*	P1	P2	P3	P4	P5	P6
Decomposition of Variance for Log Real GNP							
1	1.397	68.562	2.638	16.101	2.304	10.355	0.036
4	3.229	65.940	3.001	7.883	10.590	12.382	0.202
8	6.512	76.347	1.829	5.231	9.739	5.671	1.180
12	11.33	87.481	1.549	4.148	3.808	2.020	0.992
16	15.25	90.348	2.204	3.191	2.109	1.127	1.018
Decomposition of Variance for Inflation							
1	1.895	88.059	4.006	3.774	3.118	0.475	0.564
4	2.960	87.268	5.249	3.631	2.449	0.810	0.591
8	3.262	85.938	6.378	3.177	2.109	1.811	0.584
12	3.344	82.780	6.887	4.184	2.576	3.004	0.566
16	3.563	79.982	6.577	6.399	3.197	3.297	0.546

(continued)

(Table 5 continued)

Step	Standard Error*	Percentage of Forecast Error Variance Due to P1	P2	P3	P4	P5	P6
Decomposition of Variance for T-bills							
1	1.014	5.079	3.178	72.469	10.348	8.502	0.421
4	1.707	11.844	2.776	67.770	12.356	4.892	0.359
8	2.135	25.955	4.845	50.991	10.682	6.636	0.888
12	2.354	23.839	6.789	48.856	8.855	9.919	1.739
16	2.866	31.584	6.907	45.791	6.260	7.796	1.658
Decomposition of Variance for the Dollar							
1	1.334	70.834	6.276	1.137	12.521	8.373	0.856
4	2.416	64.857	3.591	5.969	12.793	12.351	0.436
8	3.002	50.311	2.552	15.990	12.502	18.356	0.288
12	3.551	38.076	2.459	29.459	10.169	19.583	0.251
16	4.364	42.693	2.864	32.195	7.635	14.425	0.185
Decomposition of Variance for the Base/Debt Ratio							
1	1.107	29.167	48.865	0.379	15.092	1.317	5.177
4	3.571	29.135	44.006	1.565	17.622	4.117	3.552
8	5.650	33.380	29.074	1.441	23.289	10.811	2.003
12	10.60	67.019	9.911	4.581	11.595	5.455	1.436
16	18.02	81.791	3.538	5.435	6.137	2.052	1.044
Decomposition of Variance for Deficit/GNP Ratio							
1	0.9963	0.379	88.185	0.216	0.163	0.100	10.954
4	1.532	1.289	61.606	13.803	0.208	1.531	21.560
8	2.084	16.671	41.493	13.728	8.501	1.226	18.378
12	3.406	54.764	18.221	12.955	5.888	0.610	7.558
16	3.666	57.468	17.033	12.910	5.306	0.731	6.549

*Ratio of theoretical RMS of forecast error, assuming no coefficient uncertainty, to the sample standard deviation of one-step-ahead forecast errors for that variable. Ratios for one-step-ahead errors may exceed one due to empirical bias of the model's postsample forecasts.

Table 6

Out-of-Sample Forecasting Performance
Measured by Log Determinants of the
Covariance Matrix of Forecast Errors for Nonpolicy Variables
(Average percent improvements shown in parentheses.)*

	Unconditional	Conditioning on Base/Debt	Conditioning on Deficit/GNP	Both
1965:4-1983:1				
1-Step	11.29	12.95 (-20.96)	11.20 (1.06)	12.88 (-19.96)
2-Step	14.14	15.38 (-15.46)	13.95 (2.46)	15.36 (-15.31)
4-Step	16.10	17.11 (-12.71)	15.88 (2.70)	17.01 (-11.42)
6-Step	17.54	18.68 (-14.18)	17.42 (1.59)	18.49 (-11.76)
12-Step	19.36	21.22 (-23.16)	19.48 (-1.58)	21.11 (-21.80)
1975:4-1984:3				
1-Step	8.53	8.92 (-4.92)	8.45 (0.93)	8.70 (-2.22)
2-Step	11.15	11.07 (1.05)	10.79 (4.53)	10.76 (4.90)
4-Step	13.06	12.98 (1.09)	12.76 (3.76)	12.79 (3.42)
6-Step	14.86	14.71 (1.83)	14.58 (3.45)	14.45 (4.05)

*Approximate average percentage reduction in standard error of the conditional forecast over the unconditional forecast obtained by taking the difference in log determinants and multiplying by 12.75 (divide by 8 to get standard errors for 4 variables and multiply by 100 to get percent). A negative number indicates a deterioration of forecasting performance relative to the unconditional forecast.

Table 7

Out-of-Sample Forecasting Performance
Measured by Log Determinants of the
Covariance Matrix of Forecast Errors for Nonpolicy Variables

(Average percent improvements shown in parentheses.)*

	Unconditional	DLS**	Conditional Naive Sequential+	Ideal++
1975:4-1984:3				
1-Step	8.53	8.70 (-2.22)	8.26 (3.38)	8.26 (3.38)
2-Step	11.15	10.76 (4.90)	10.77 (4.83)	8.76 (37.98)
4-Step	13.06	12.79 (3.42)	12.76 (3.85)	8.54 (56.57)
6-Step	14.86	14.45 (1.83)	14.66 (2.41)	9.01 (73.06)

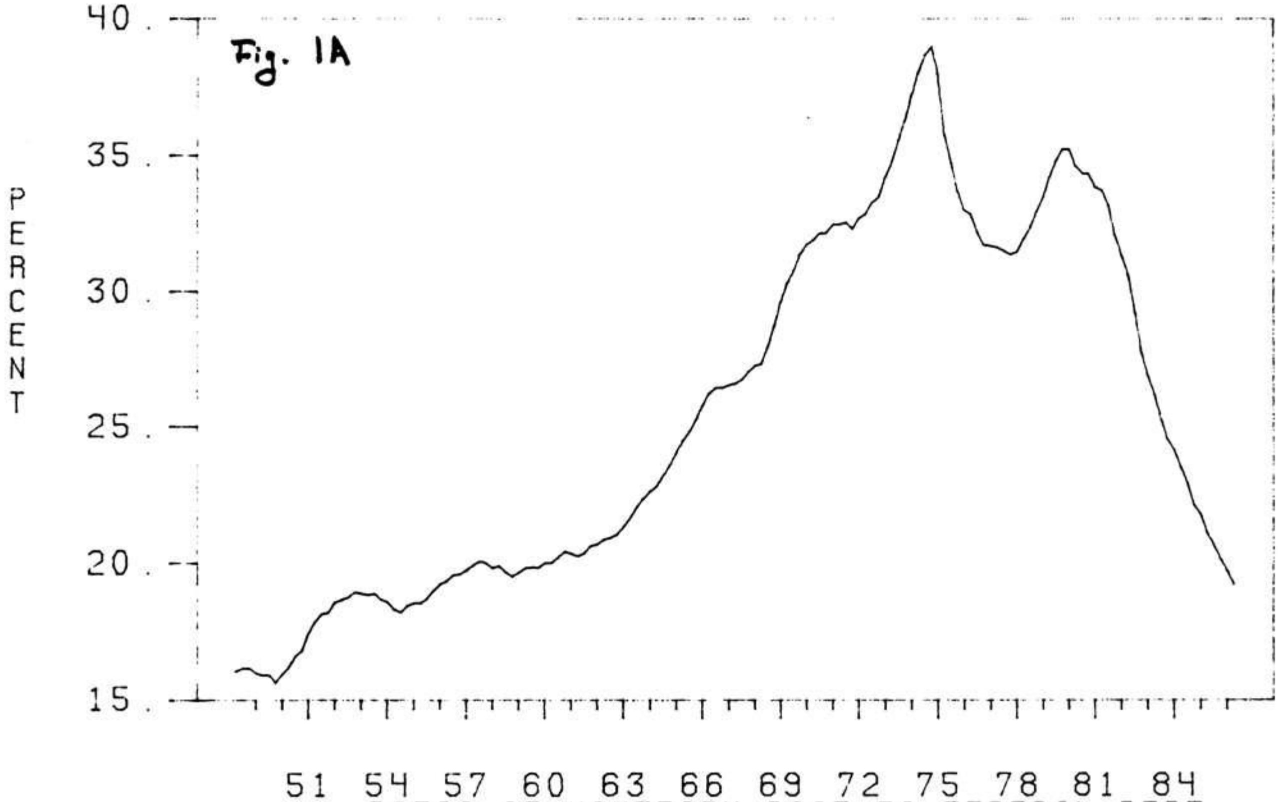
*Approximate average percentage reduction in standard error of the forecast over the unconditional forecast obtained by taking the difference in log determinants and multiplying by 12.75 (divide by 8 to get standard errors for 4 variables and multiply by 100 to get percent).

**Forecasts conditional on six future quarters of both policy variables, assuming no parameter variation.

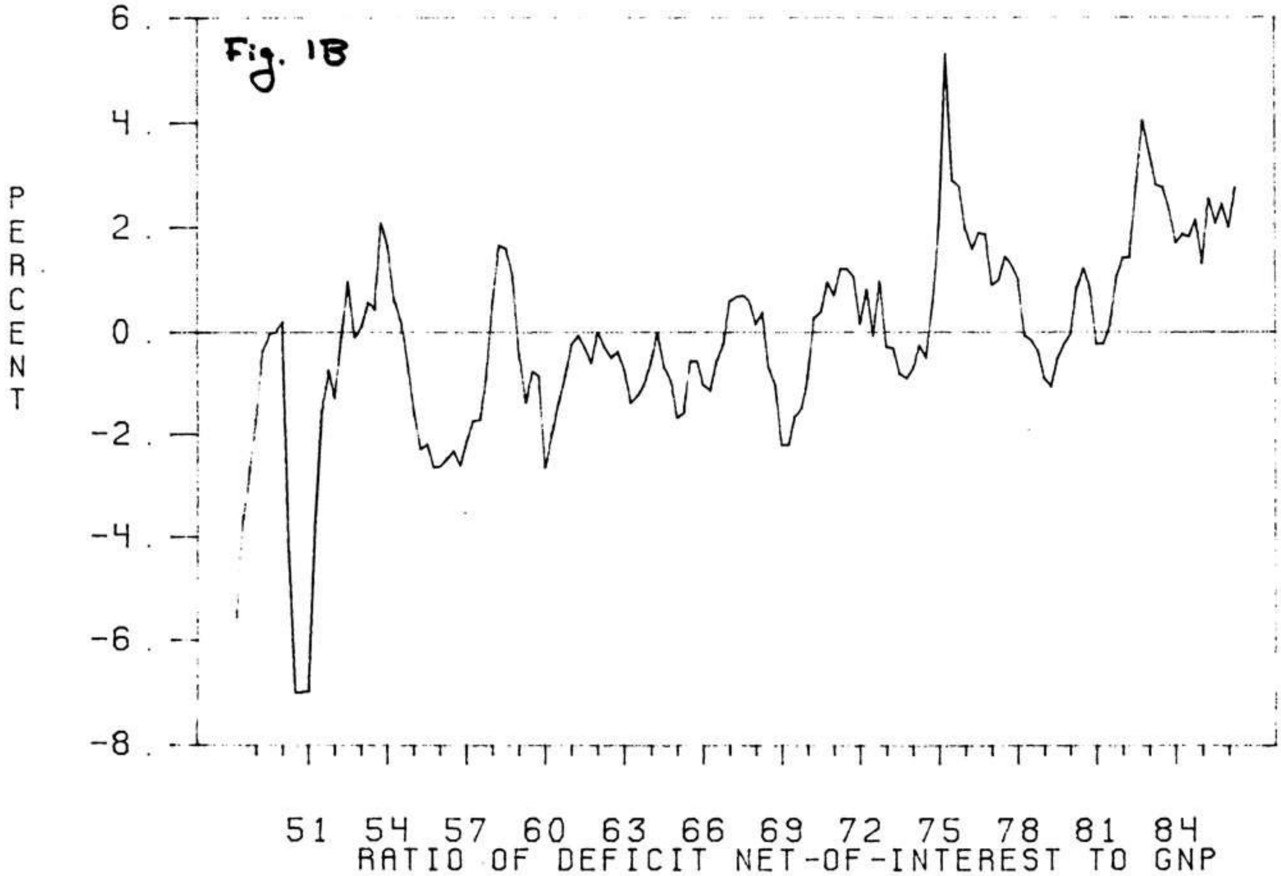
+Sequential one step ahead conditional forecasts, Kalman filtering at each step using the previous quarter's forecasts.

++Sequential one step ahead conditional forecasts, Kalman filtering at each step using the previous quarter's historical data.

DATA SERIES

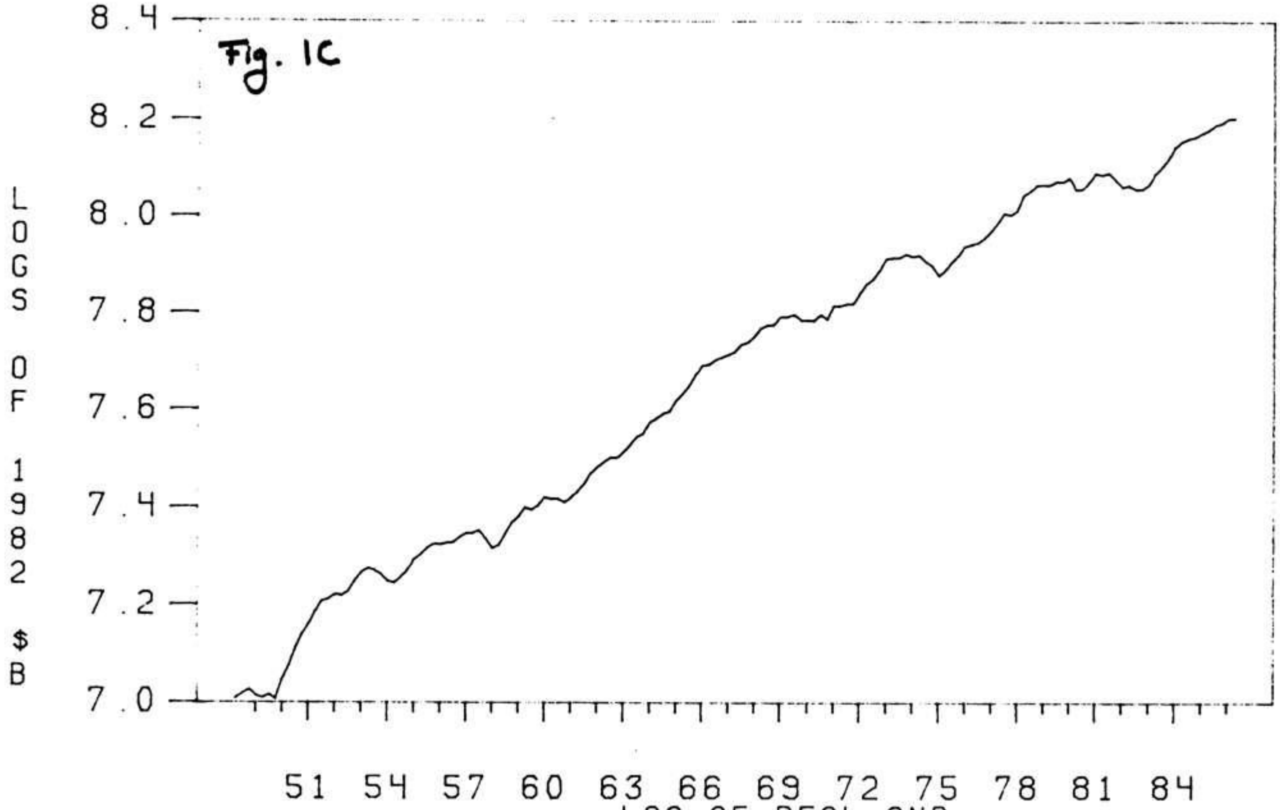


RATIO OF MONETARY BASE TO FEDERAL DEBT

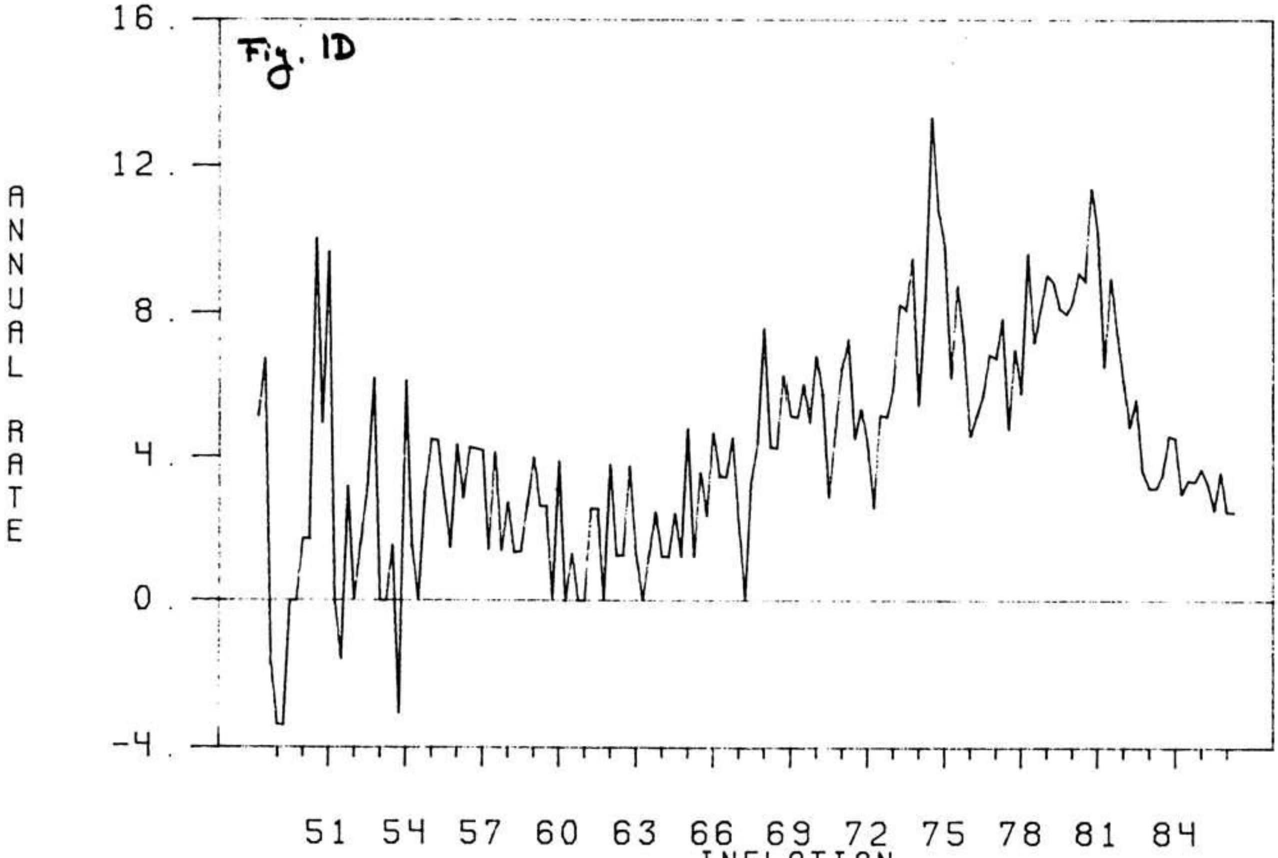


RATIO OF DEFICIT NET-OF-INTEREST TO GNP

DATA SERIES

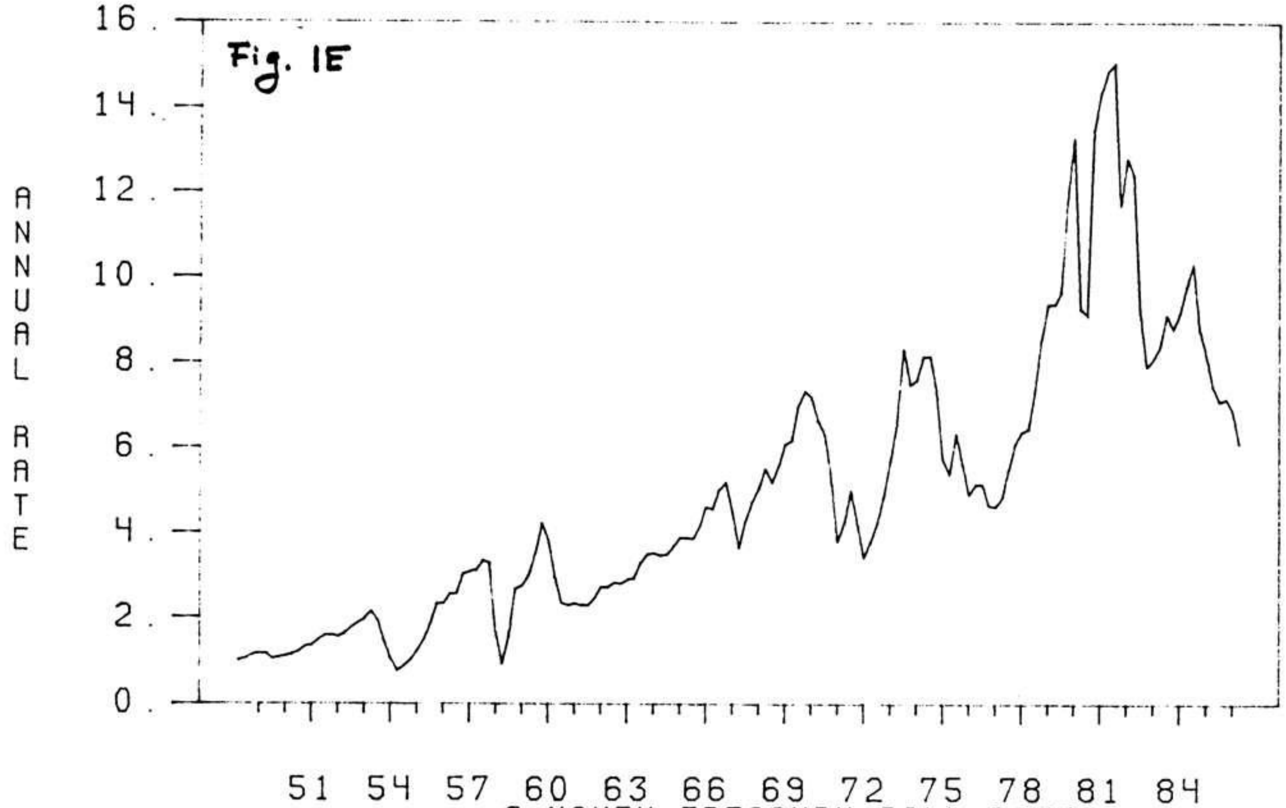


LOG OF REAL GNP

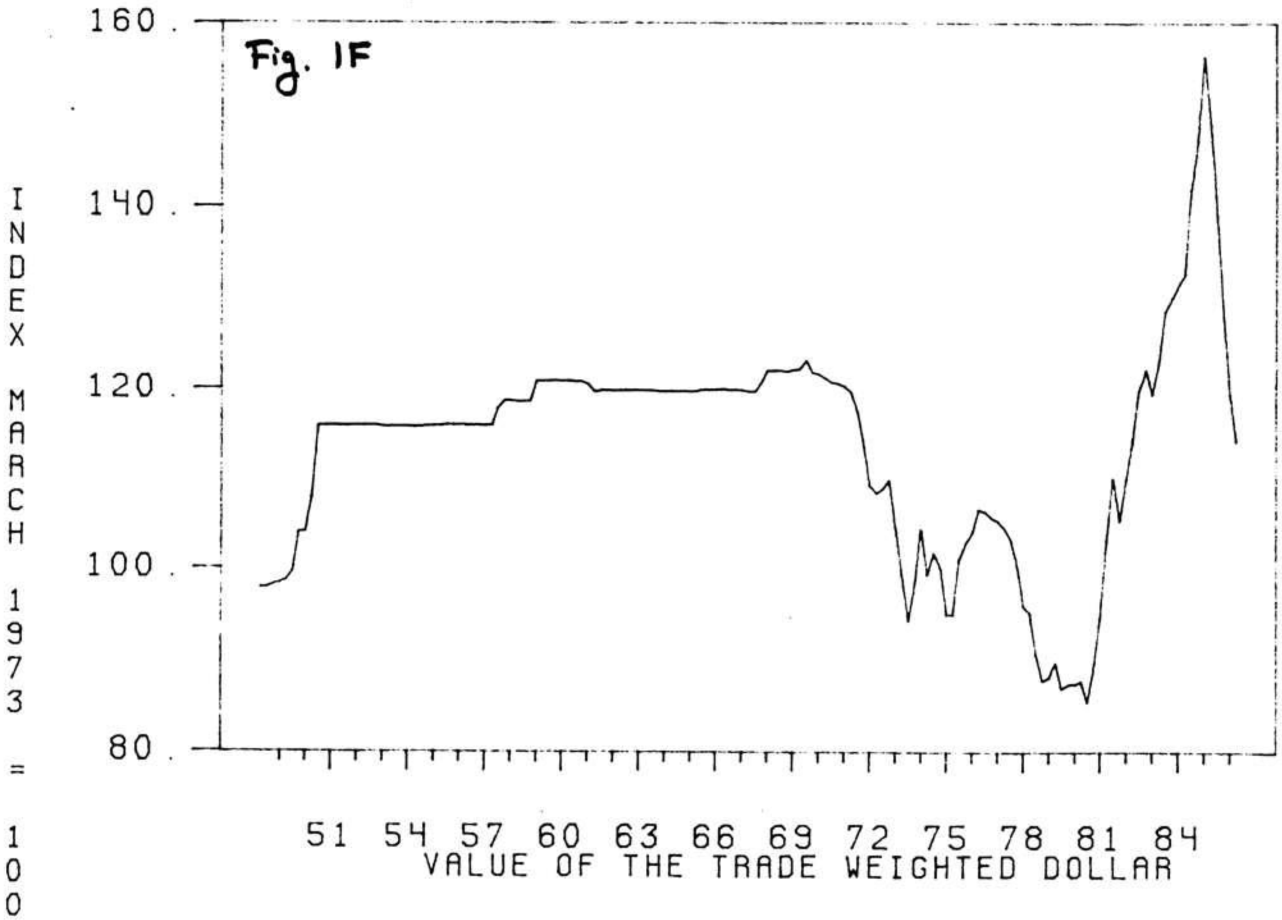


INFLATION

DATA SERIES

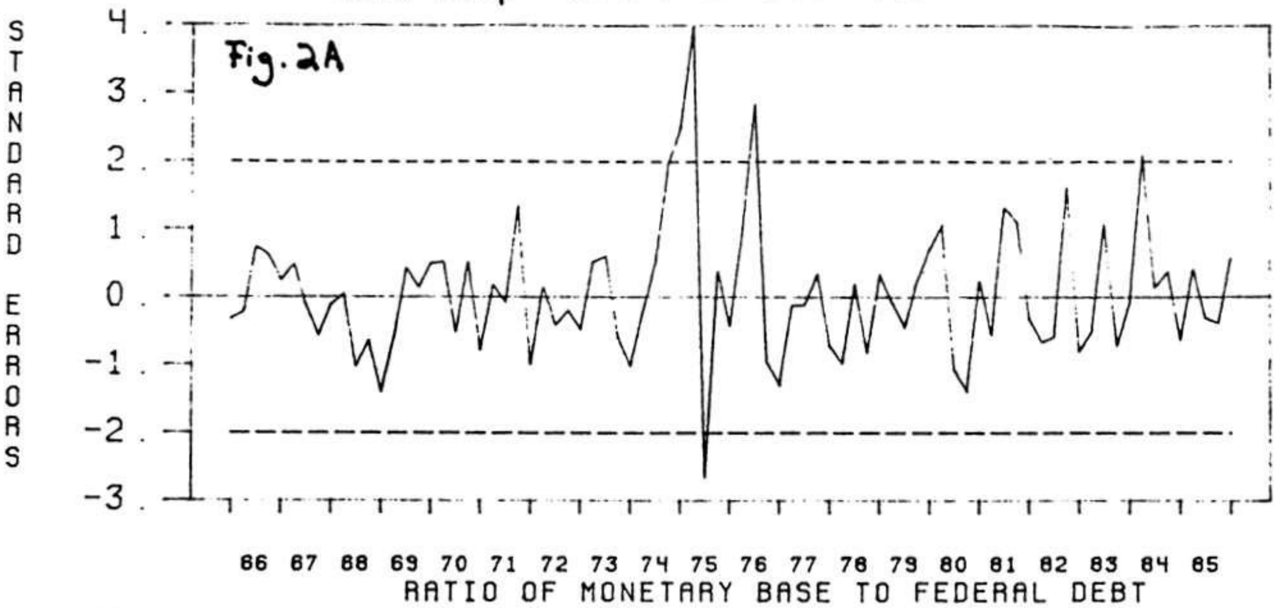


3-MONTH TREASURY BILL RATE

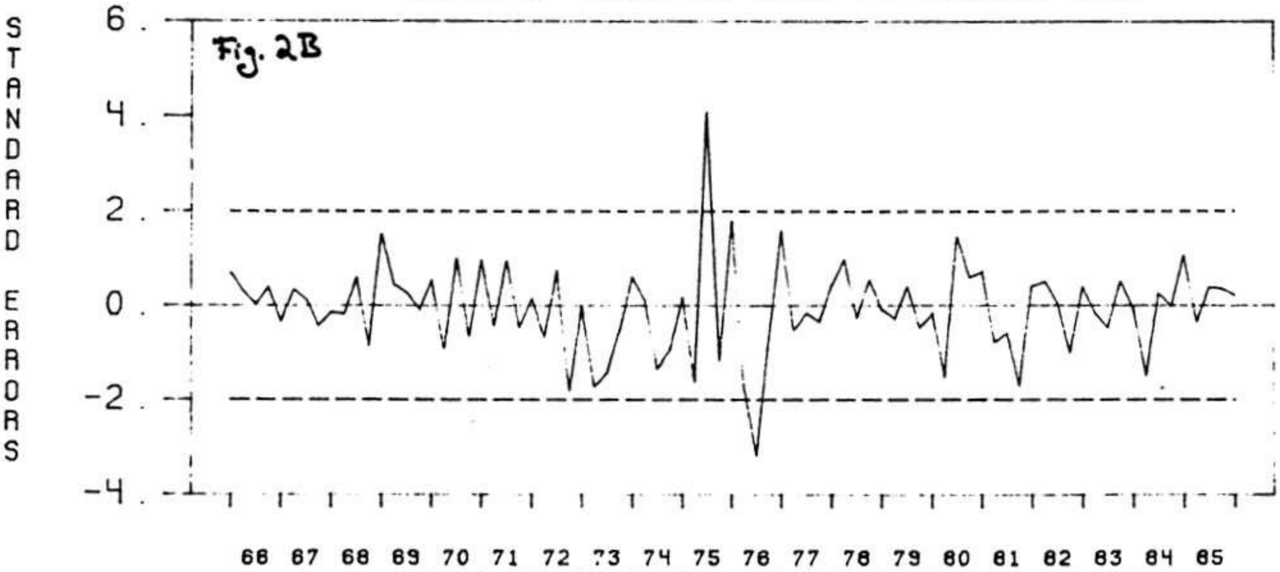


VALUE OF THE TRADE WEIGHTED DOLLAR

One Step Ahead Forecast Errors

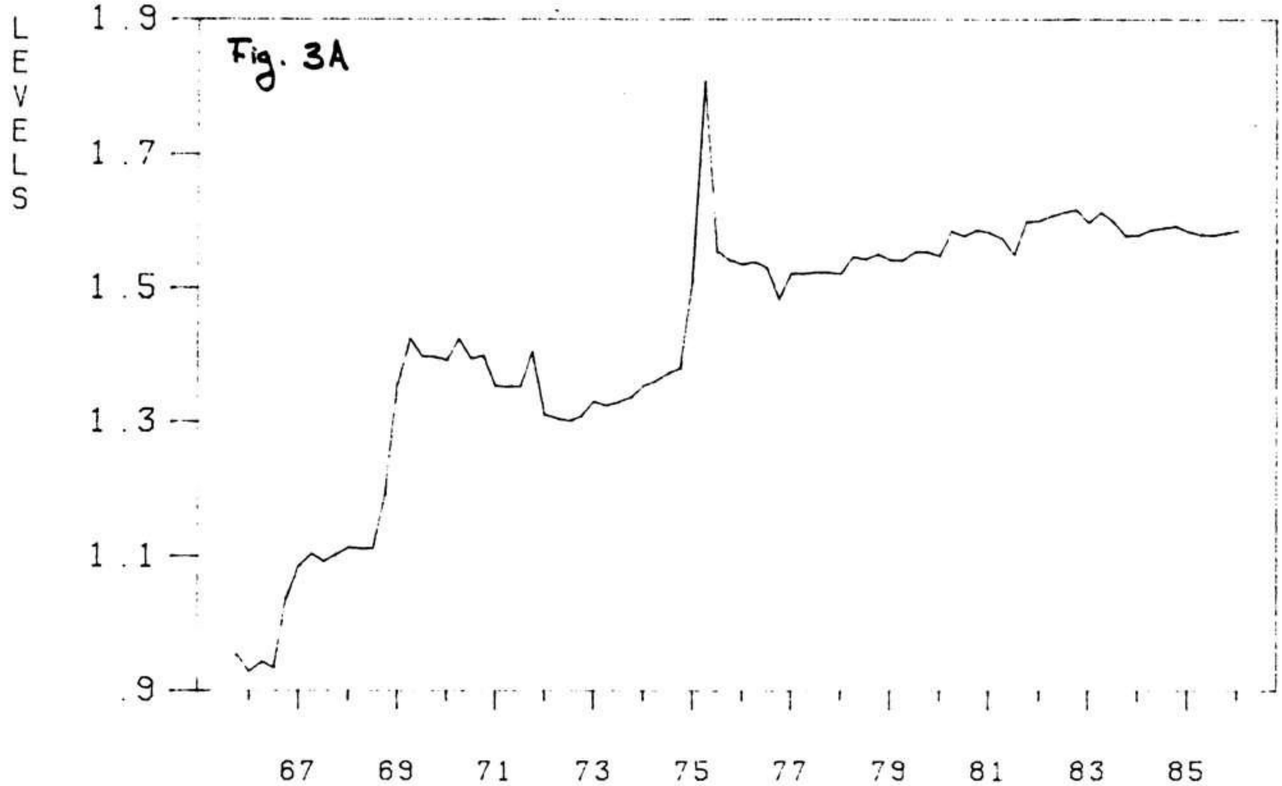


RATIO OF MONETARY BASE TO FEDERAL DEBT

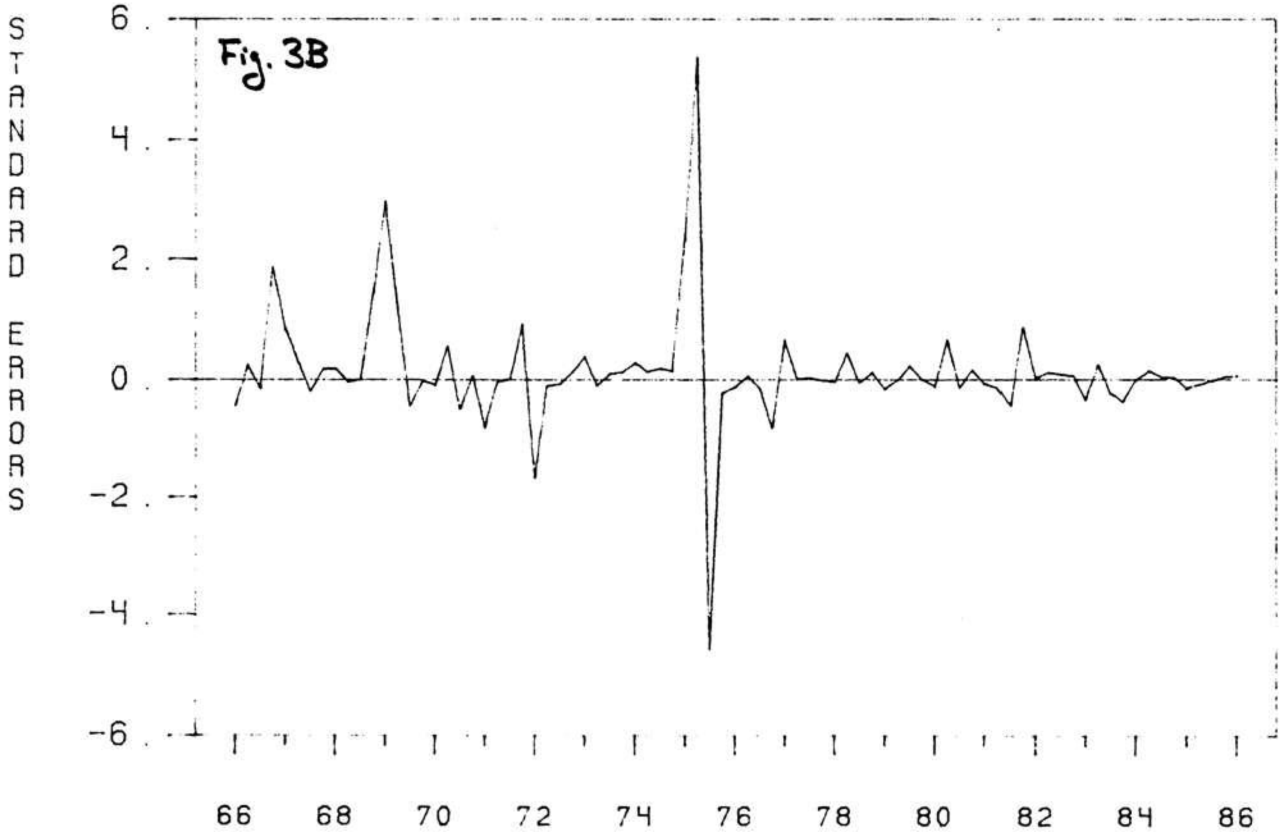


RATIO OF DEFICIT NET-OF-INTEREST TO GNP

RATIO OF MONETARY BASE TO FEDERAL DEBT

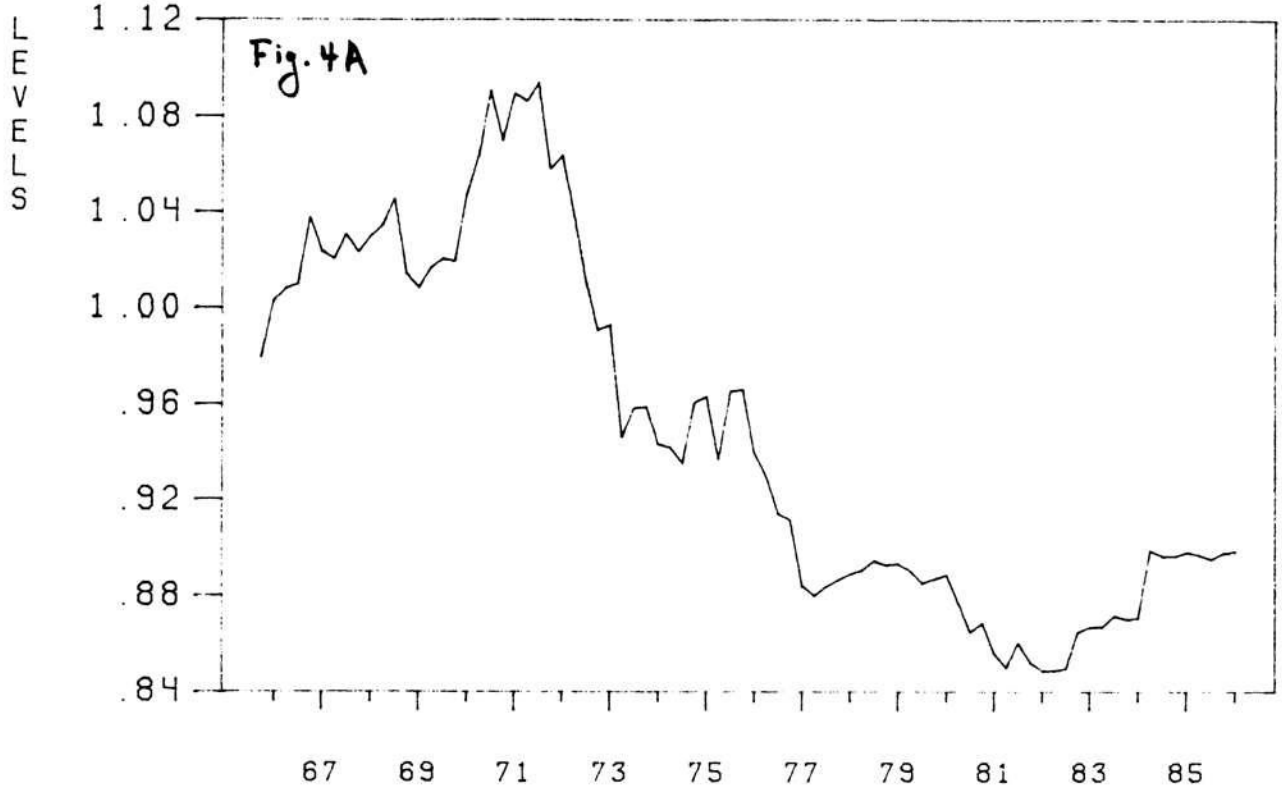


COEFFICIENT ON FIRST OWN LAG

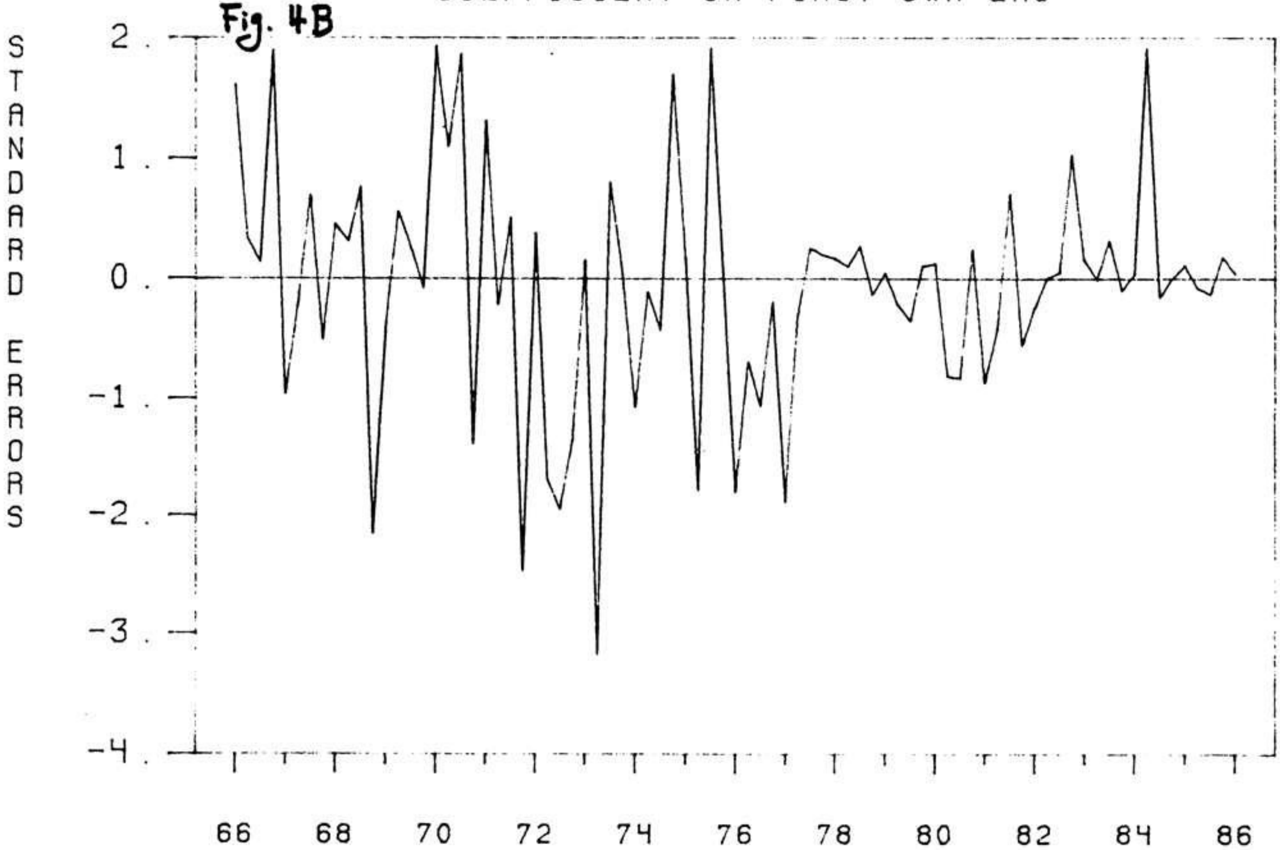


STANDARDIZED FIRST DIFFERENCES

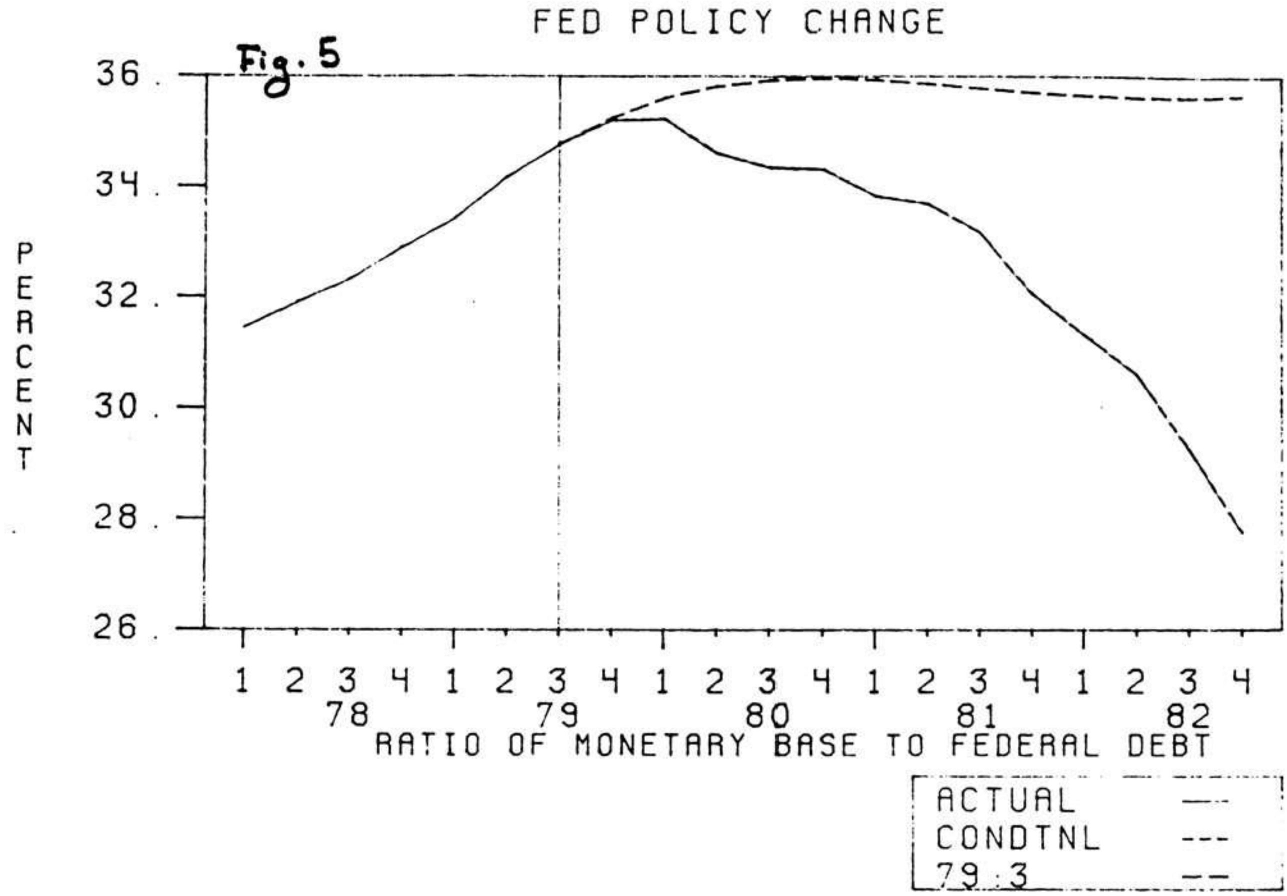
RATIO OF DEFICIT NET-OF-INTEREST TO GNP



COEFFICIENT ON FIRST OWN LAG



STANDARDIZED FIRST DIFFERENCES


FED POLICY CHANGE
Fig. 5
PERCENT
36
34
32
30
28
26
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4
78
79
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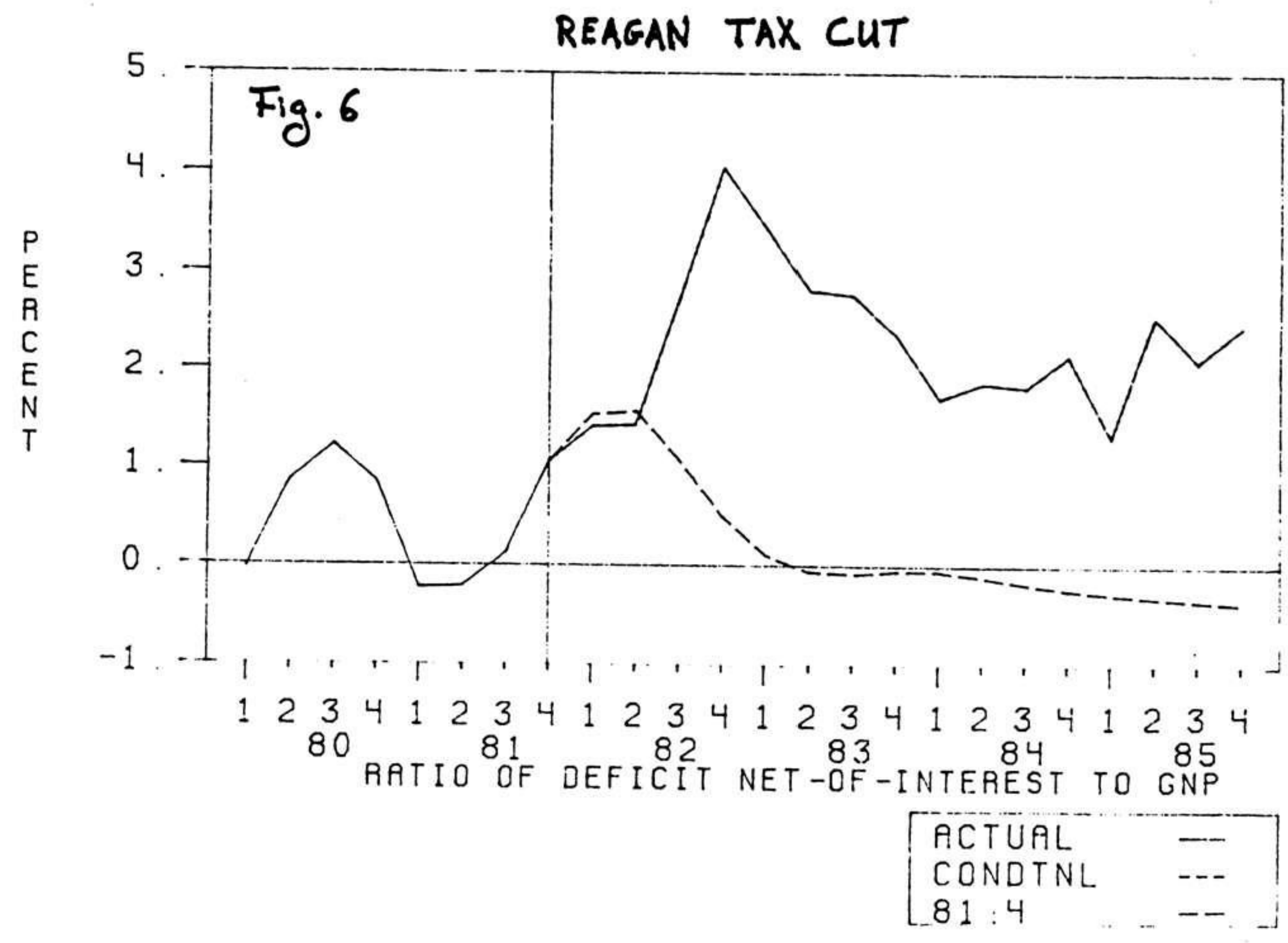
81
82
RATIO OF MONETARY BASE TO FEDERAL DEBT
ACTUAL
CONDTNL
79:3


REAGAN TAX CUT
Fig. 6
PERCENT
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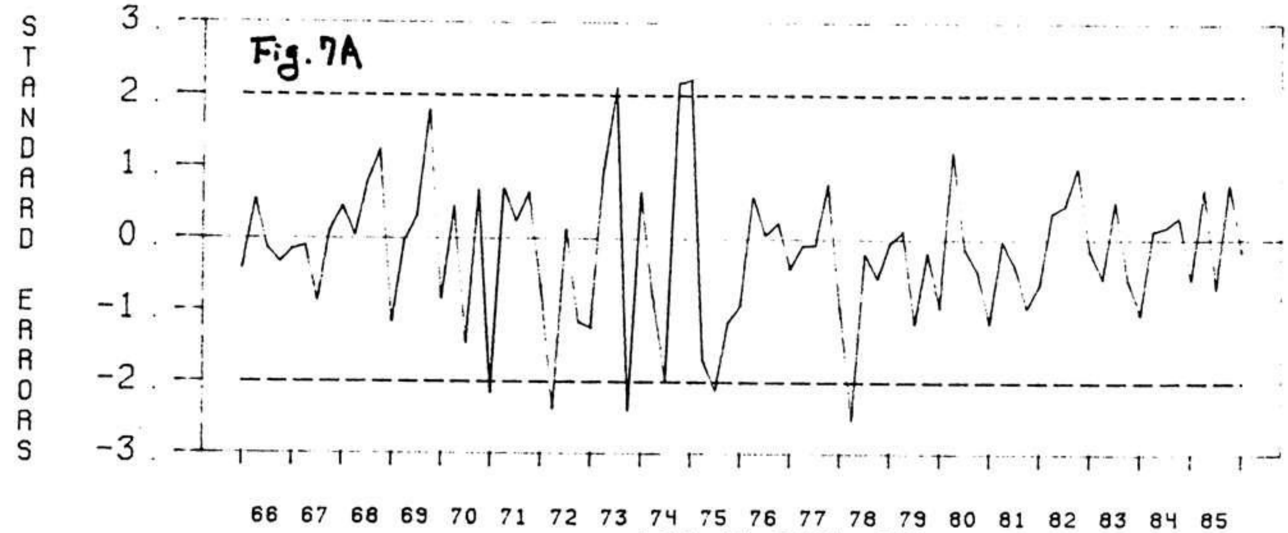
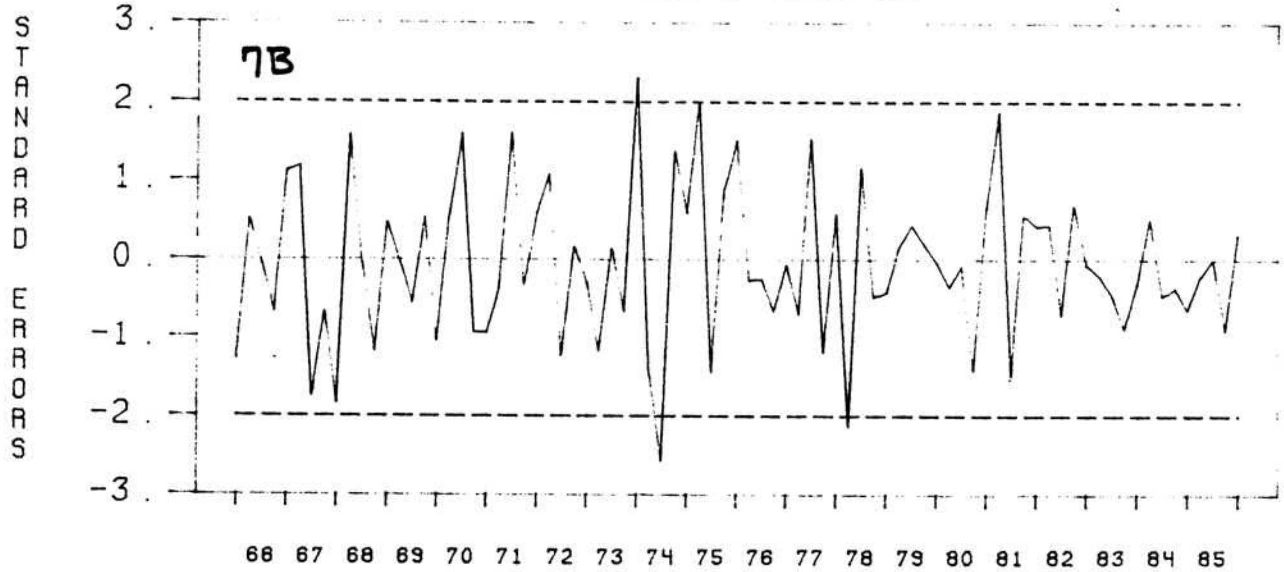
85
RATIO OF DEFICIT NET-OF-INTEREST TO GNP
ACTUAL
CONDTNL
81:4

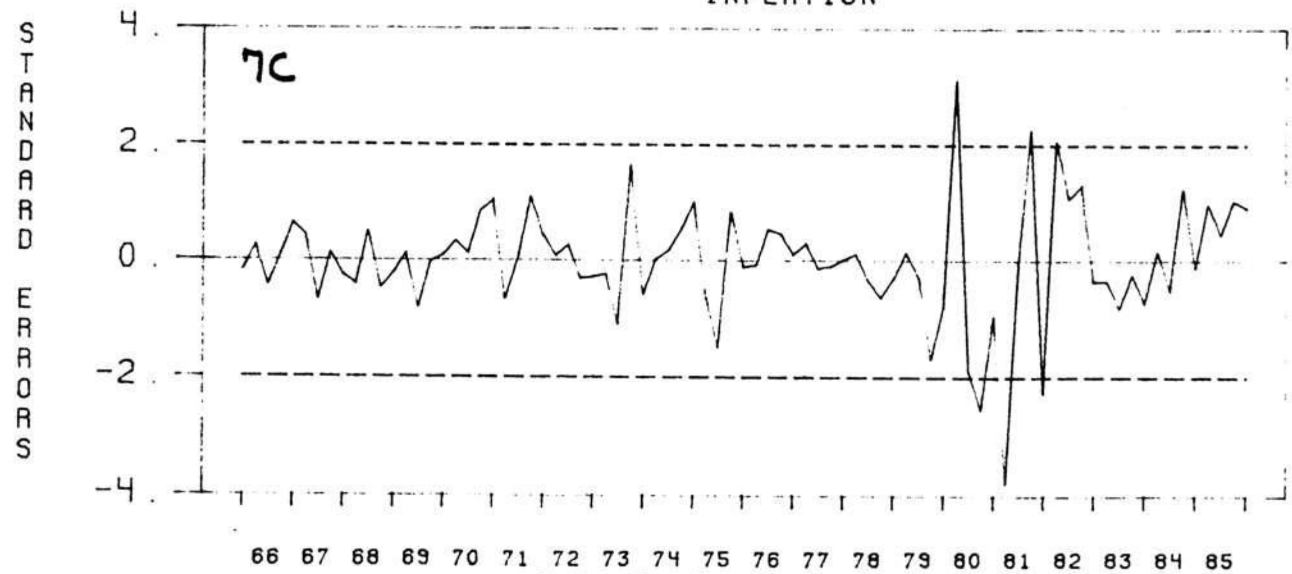
ONE STEP AHEAD FORECAST ERRORS



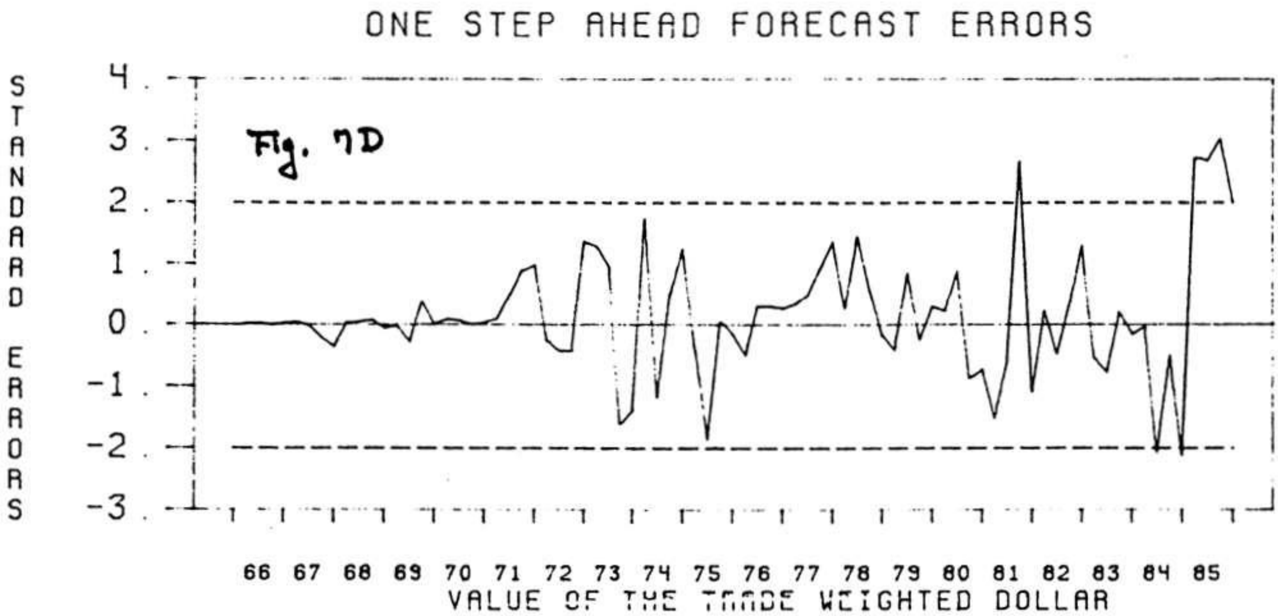
LOG OF REAL GNP



INFLATION



3-MONTH TREASURY BILL RATE


ONE STEP AHEAD FORECAST ERRORS
Fig. 7D
STANDARD ERRORS
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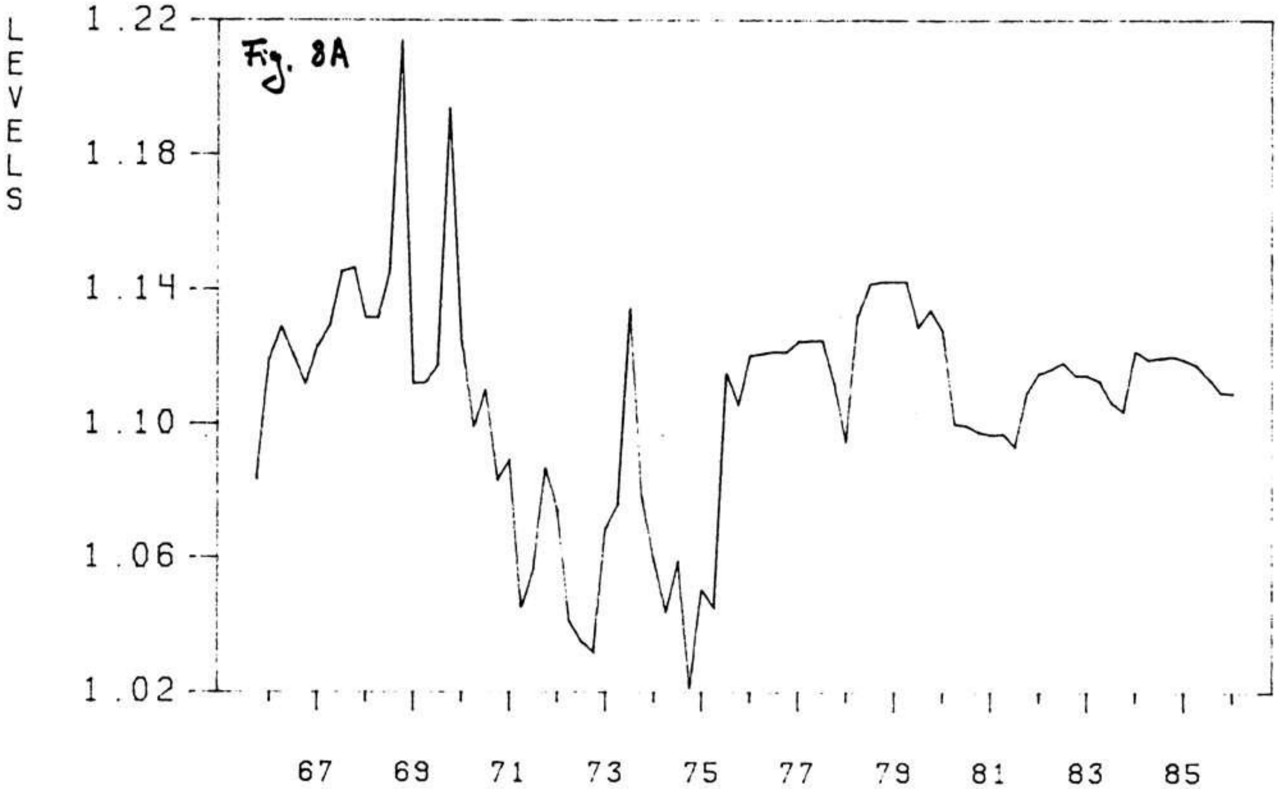
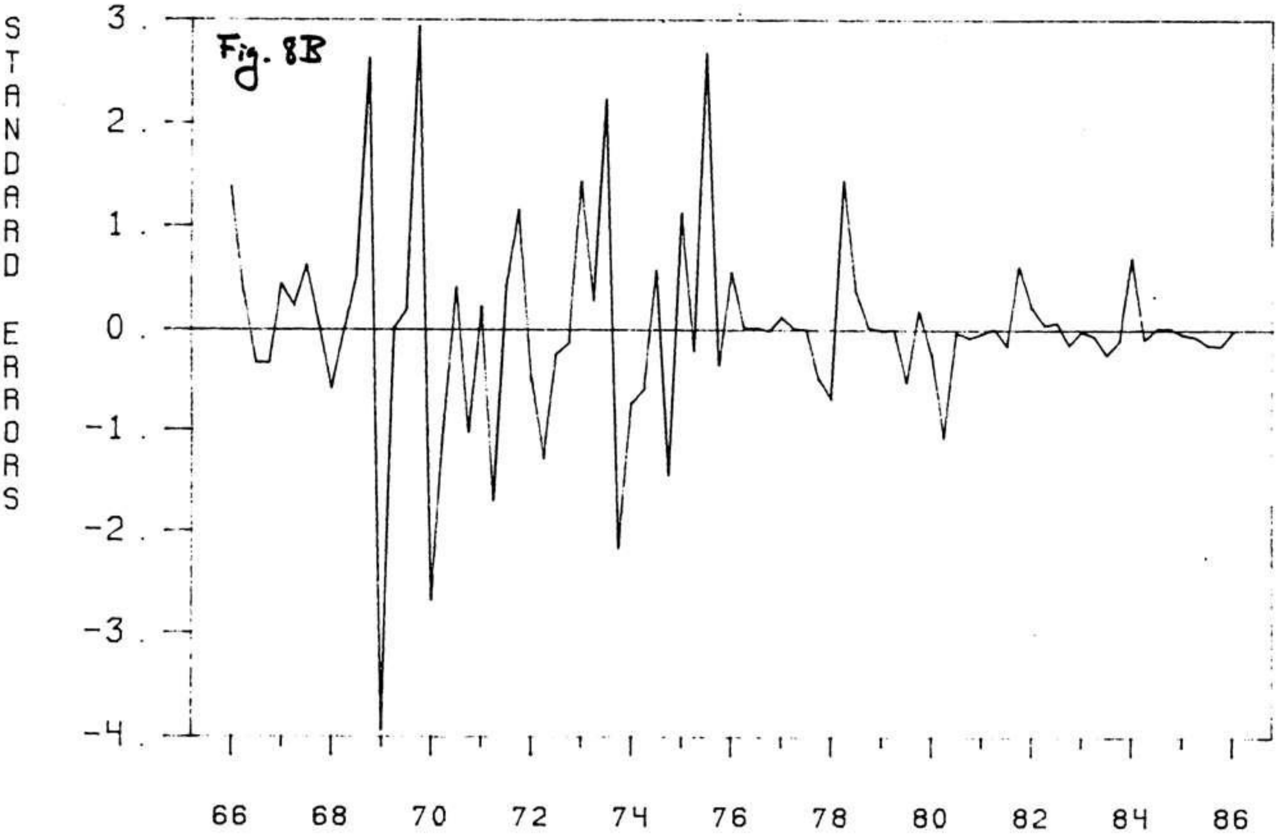
66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85
VALUE OF THE TRADE WEIGHTED DOLLAR

LOG OF REAL GNP

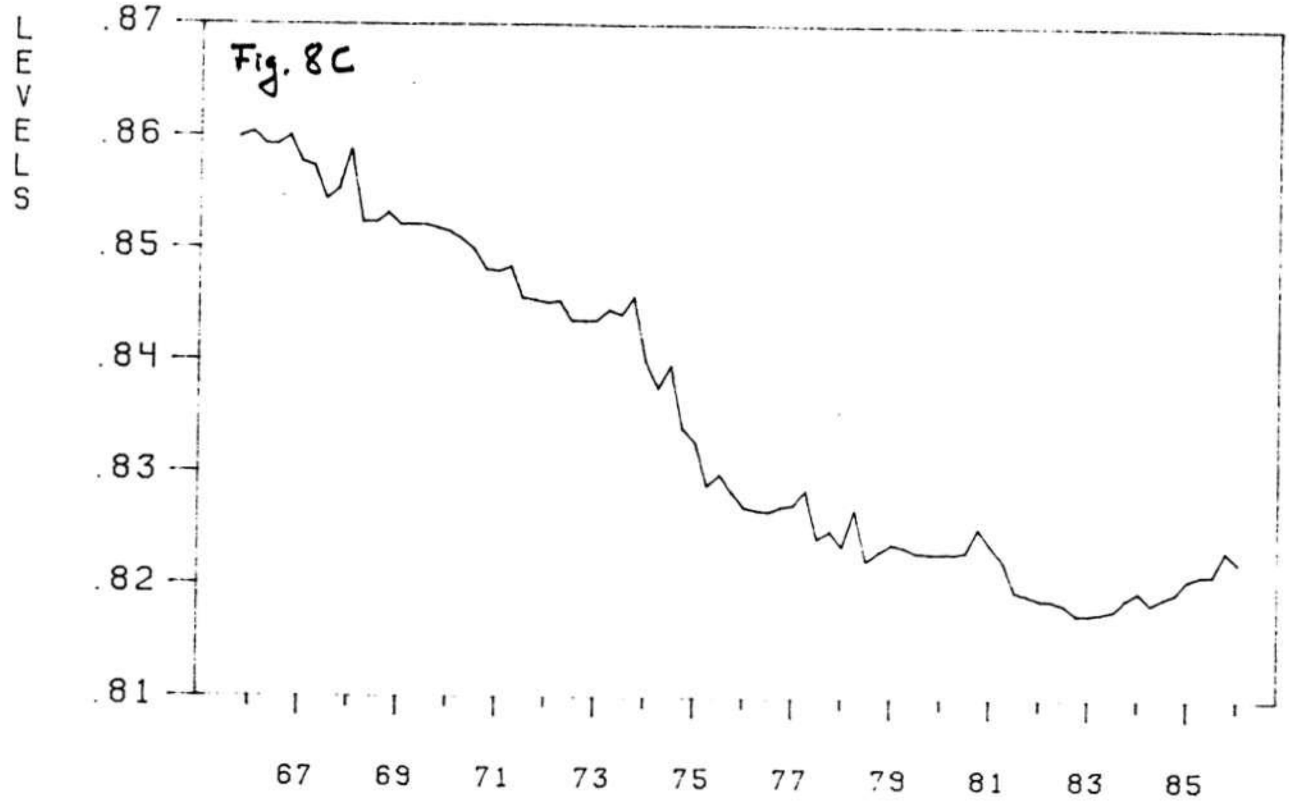


COEFFICIENT ON FIRST OWN LAG

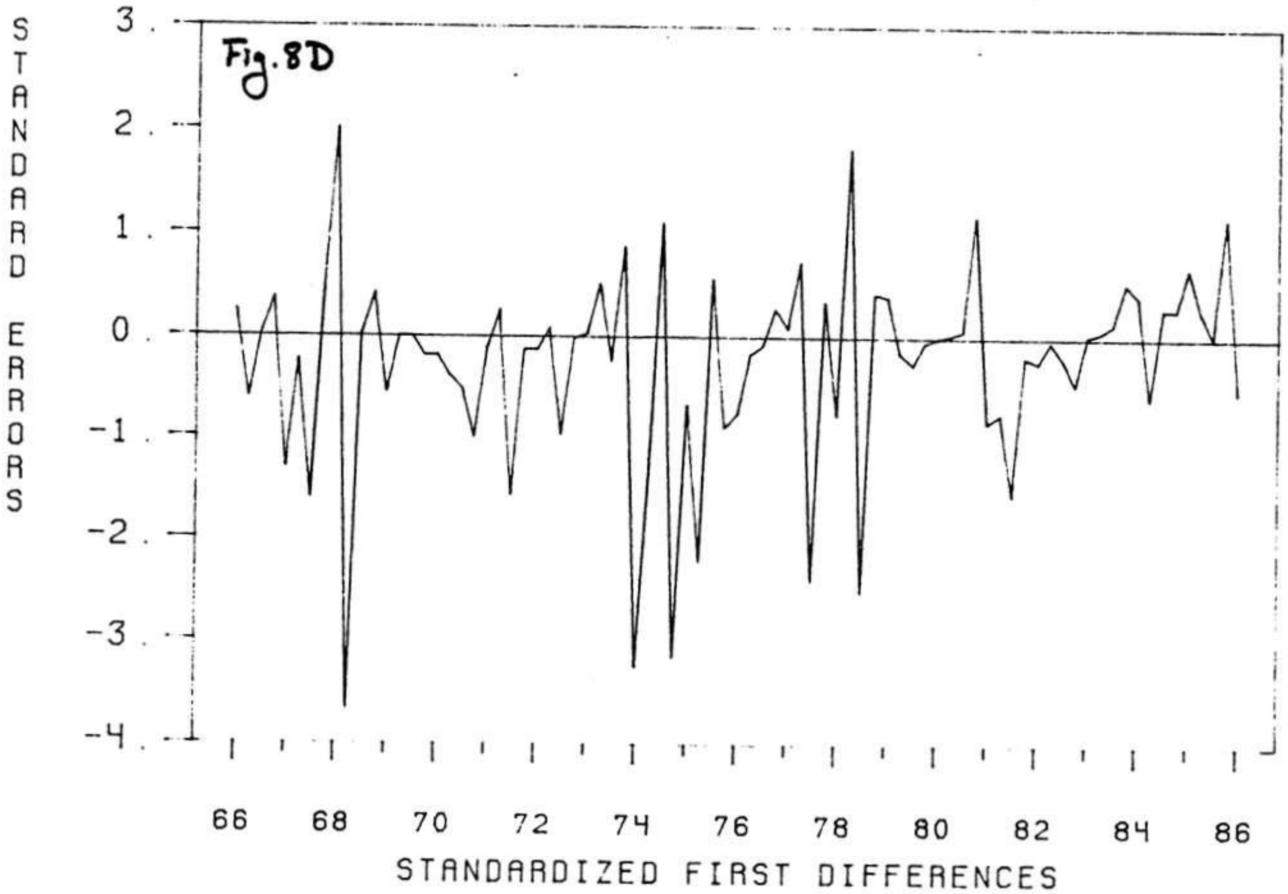


STANDARDIZED FIRST DIFFERENCES

INFLATION

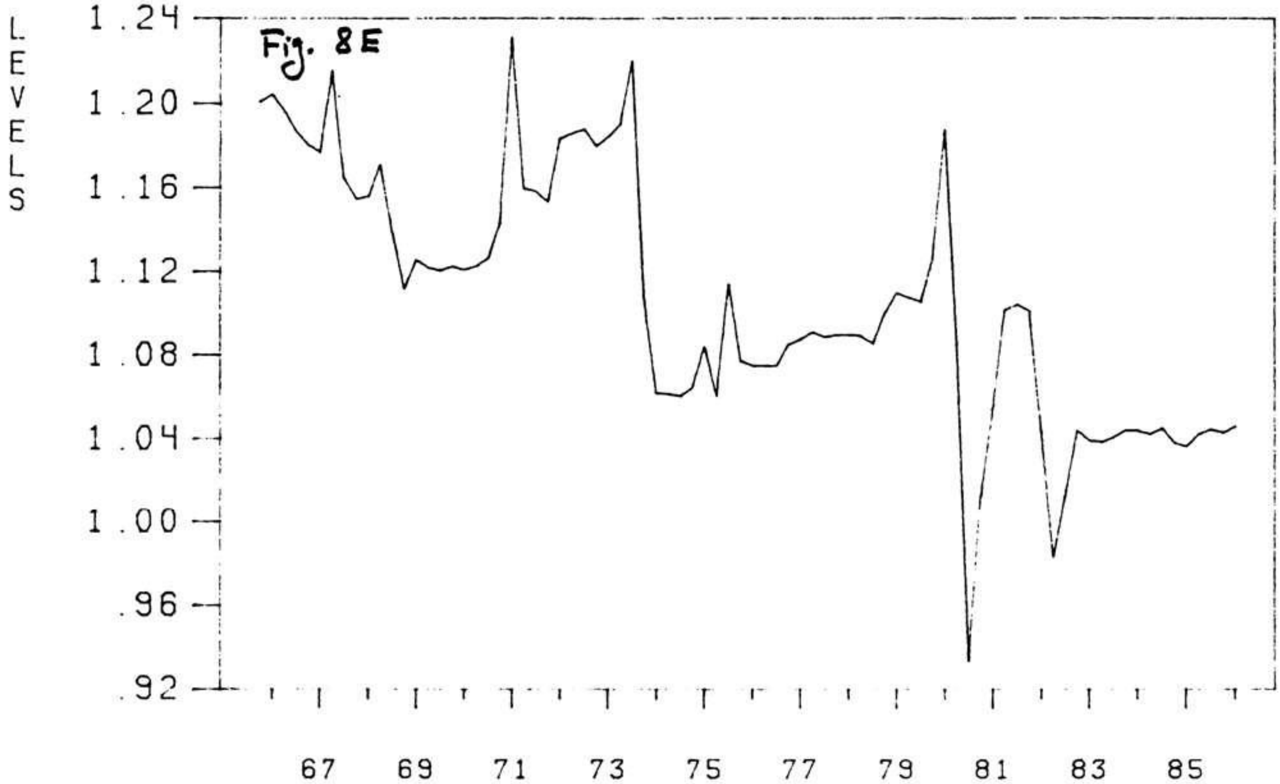


COEFFICIENT ON FIRST OWN LAG



STANDARDIZED FIRST DIFFERENCES

3-MONTH TREASURY BILL RATE



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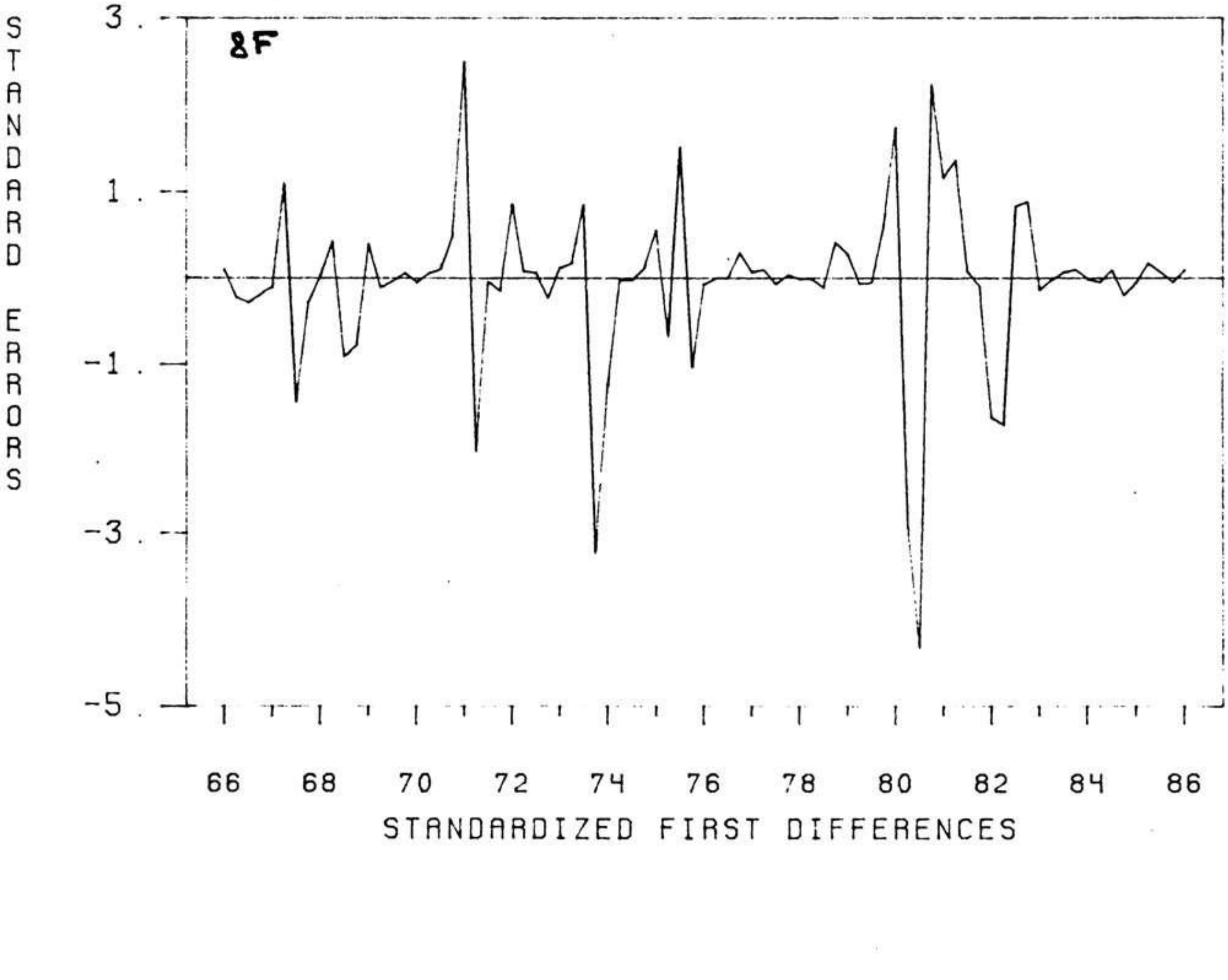
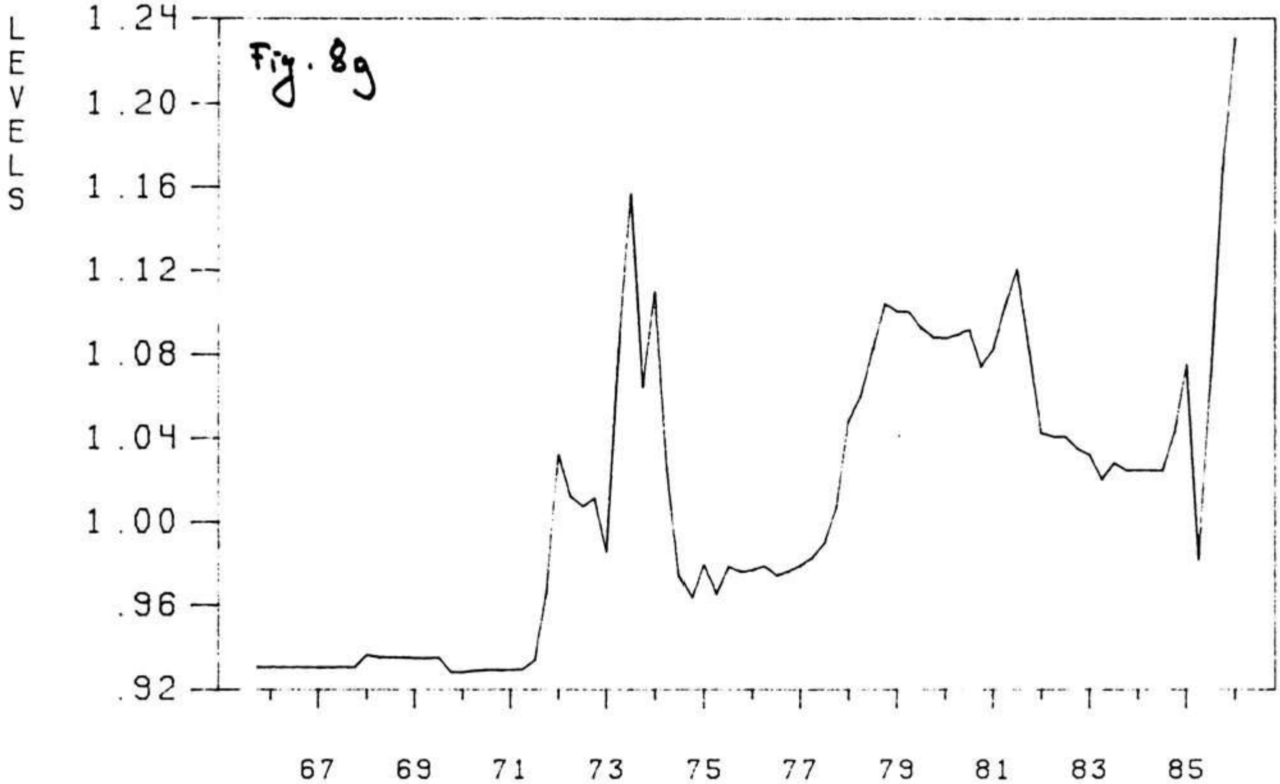
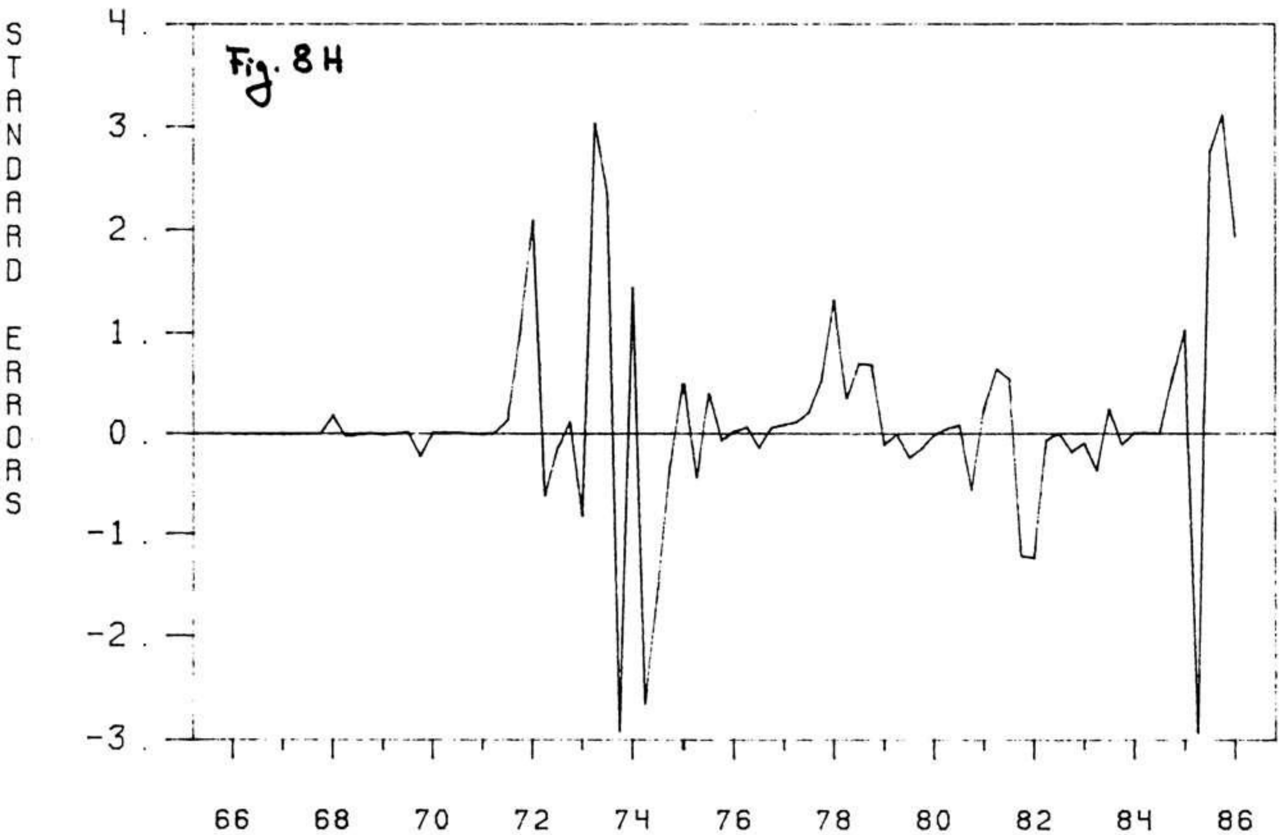


STANDARDIZED FIRST DIFFERENCES

VALUE OF THE TRADE WEIGHTED DOLLAR

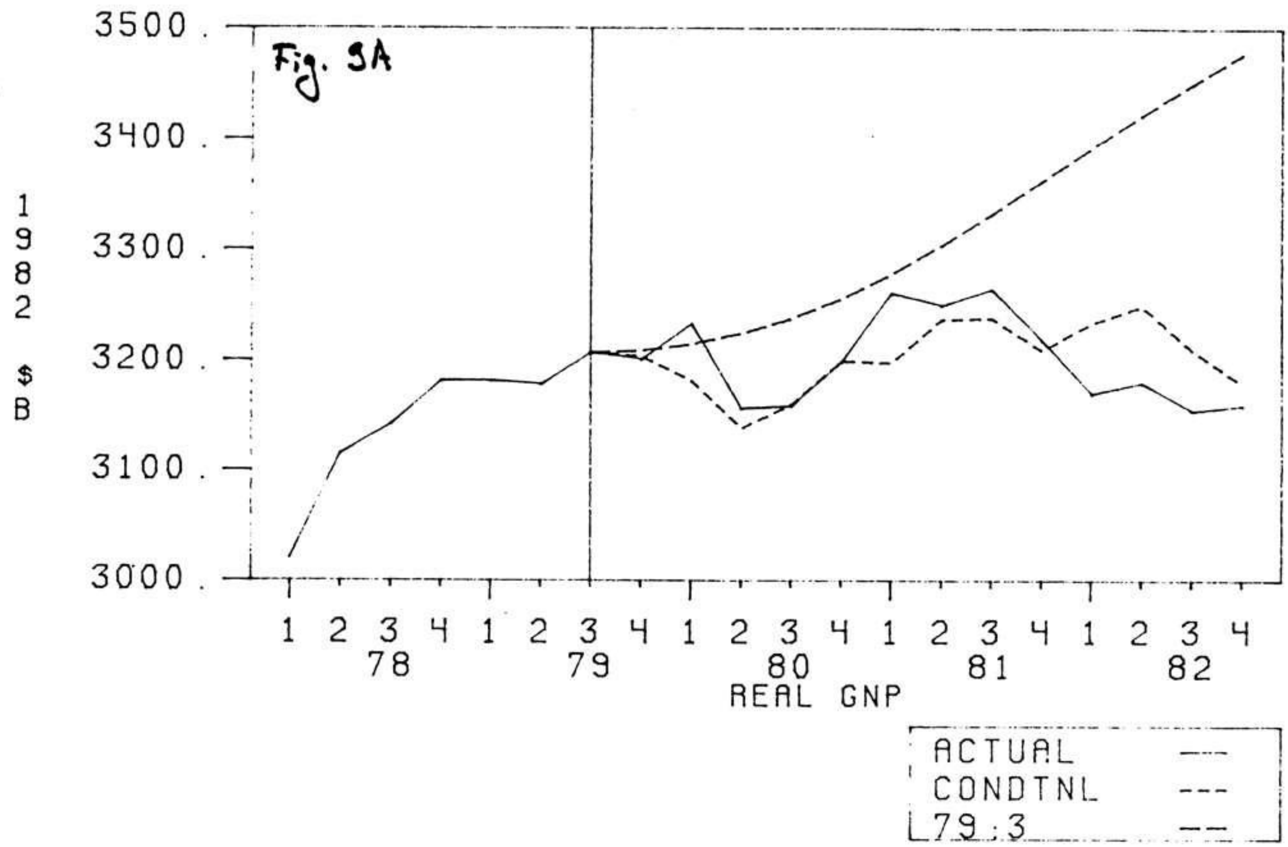


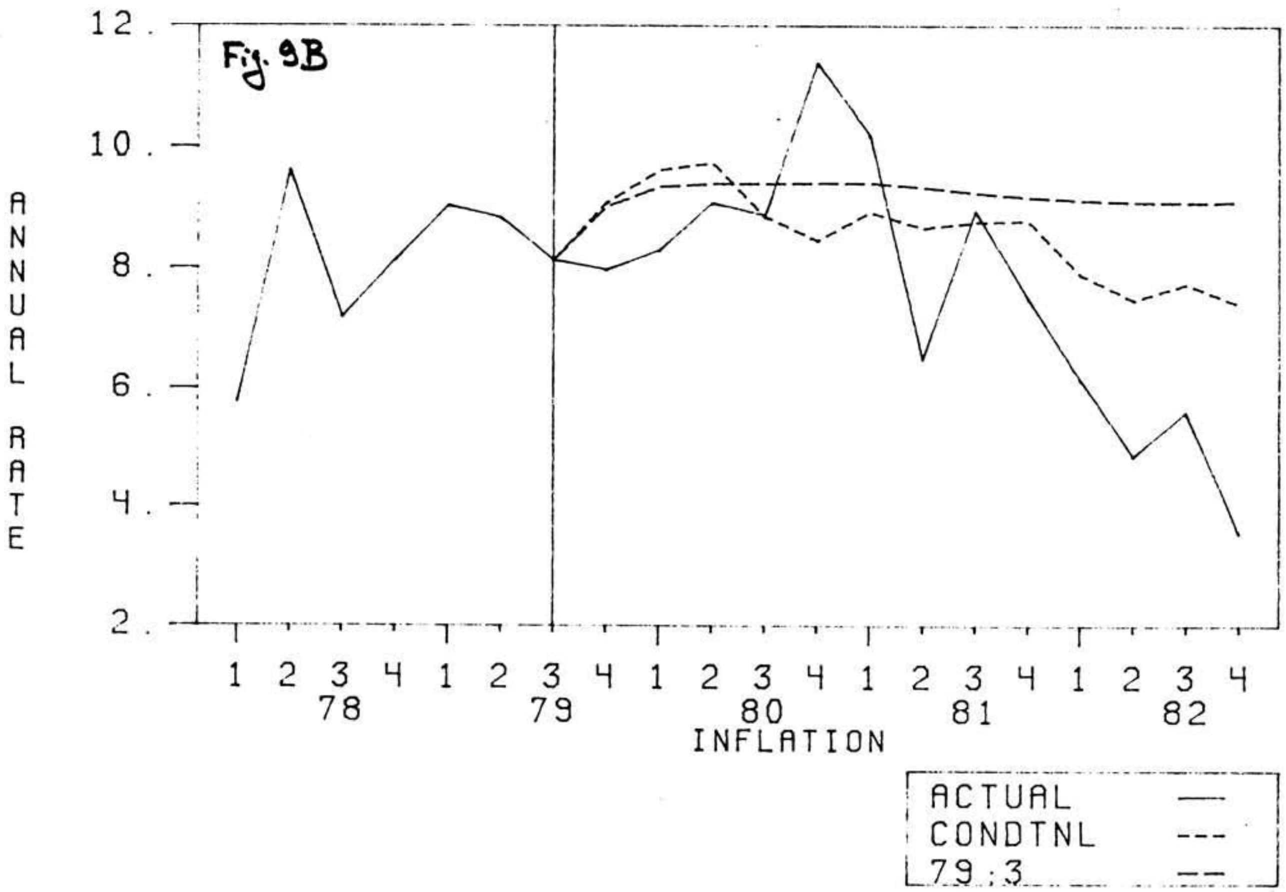
COEFFICIENT ON FIRST OWN LAG



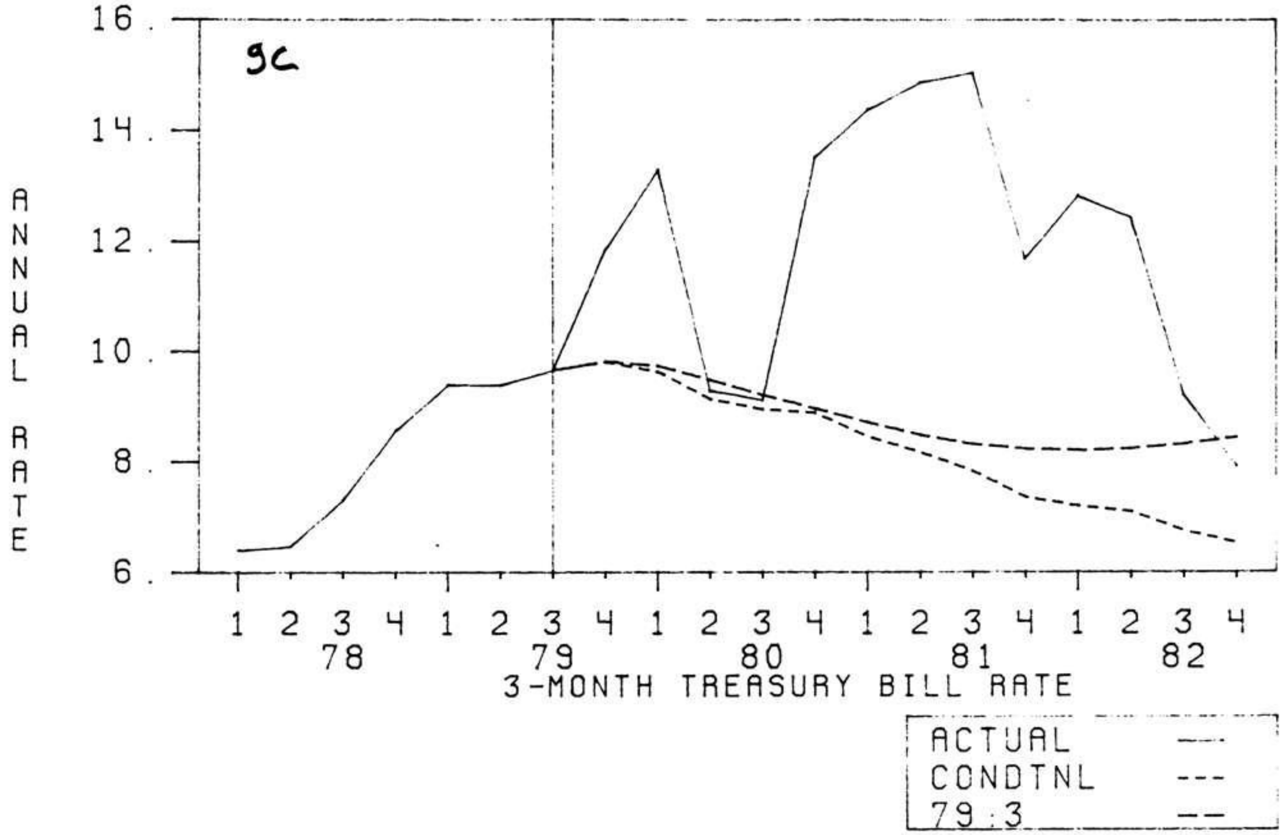
STANDARDIZED FIRST DIFFERENCES

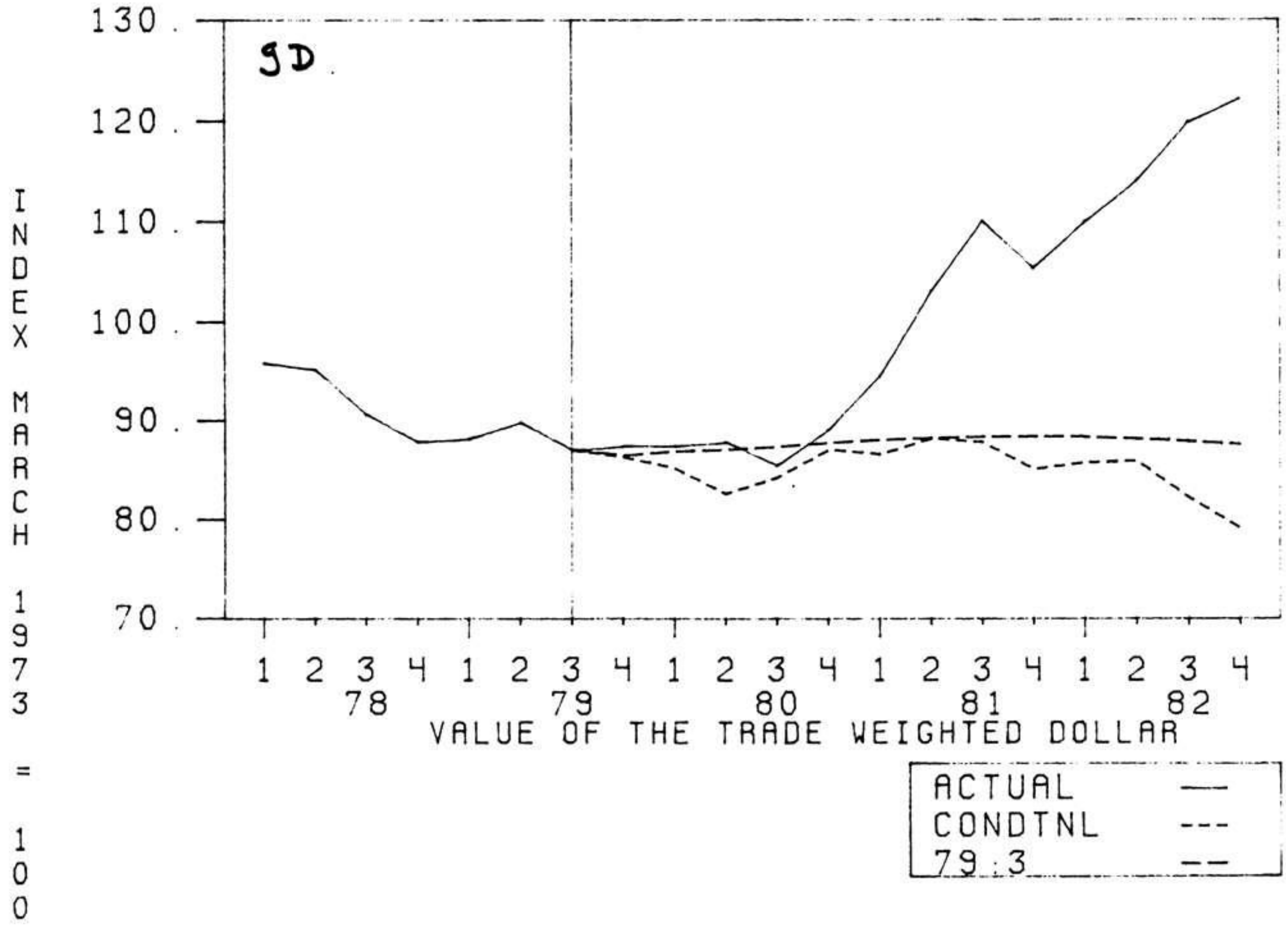
FED POLICY CHANGE

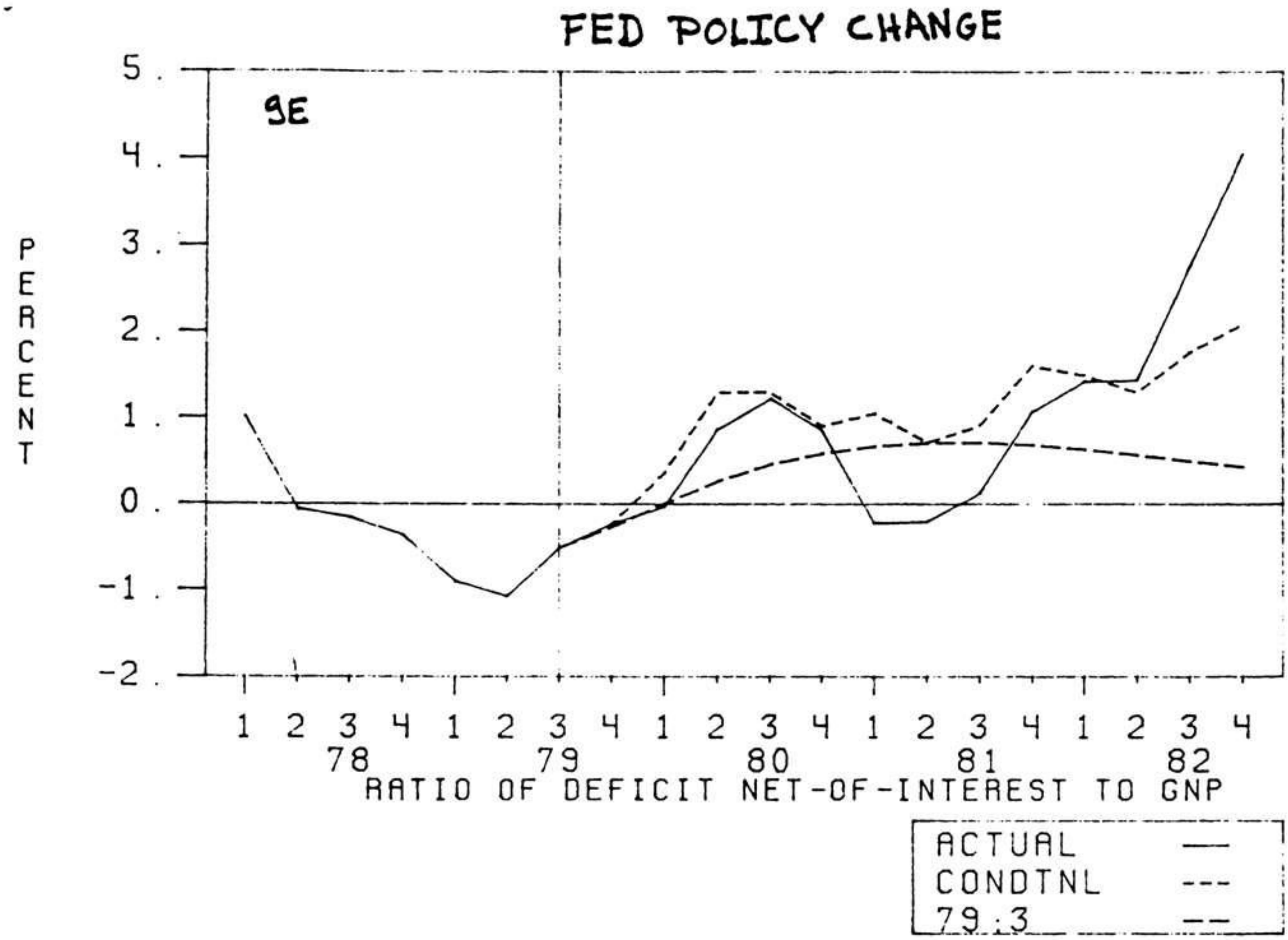




FED POLICY CHANGE






FED POLICY CHANGE
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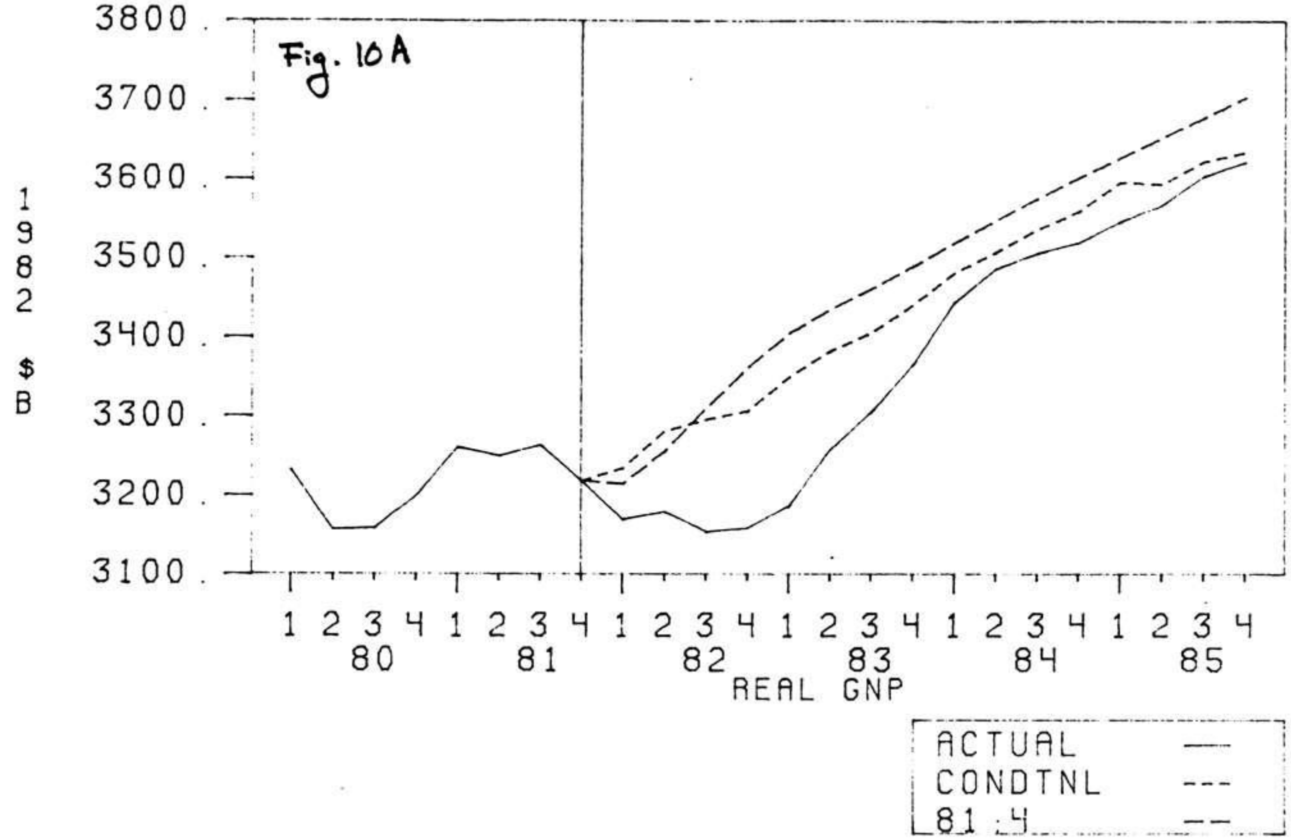
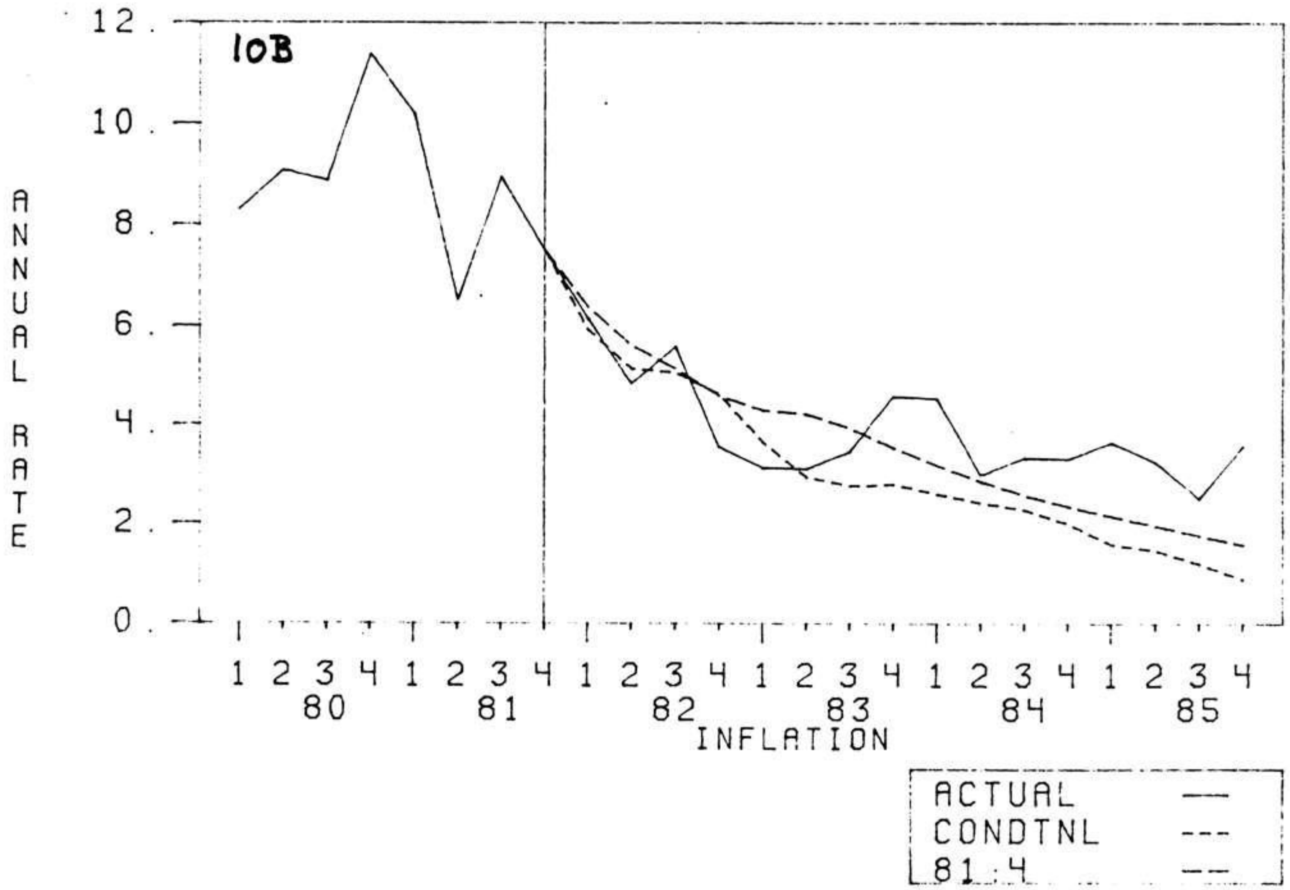
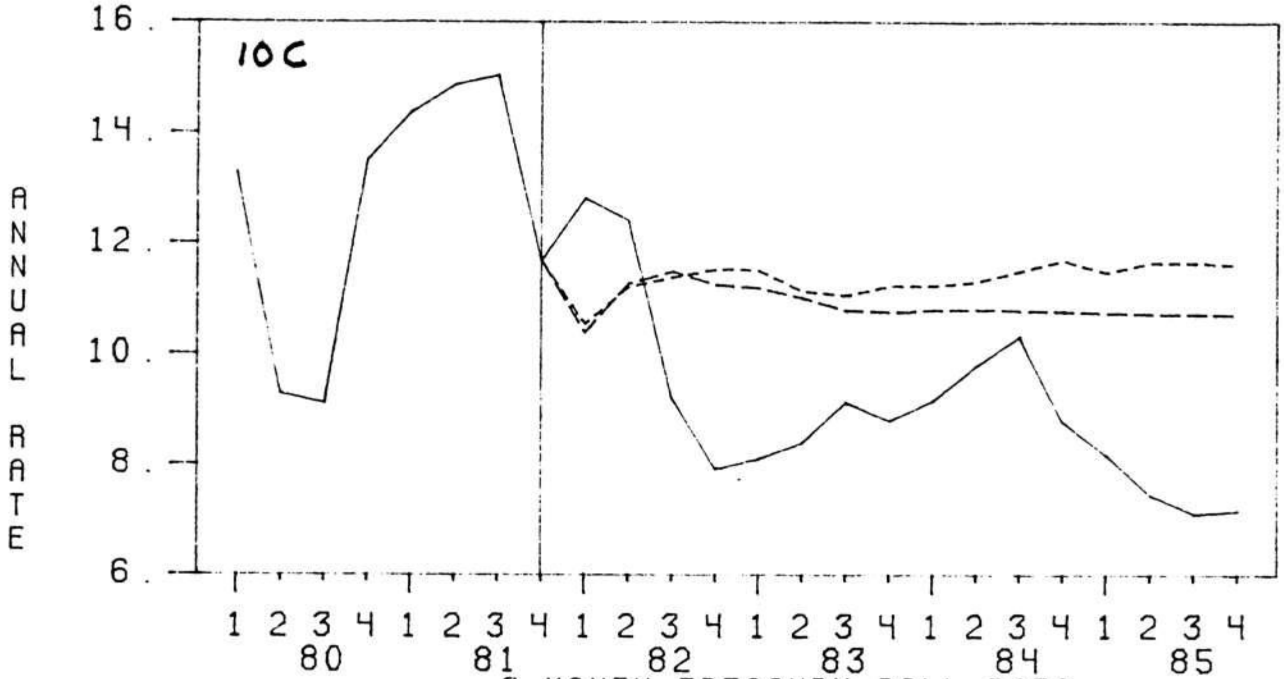
RATIO OF DEFICIT NET-OF-INTEREST TO GNP
ACTUAL
CONDTNL
79:3

REAGAN TAX CUTS

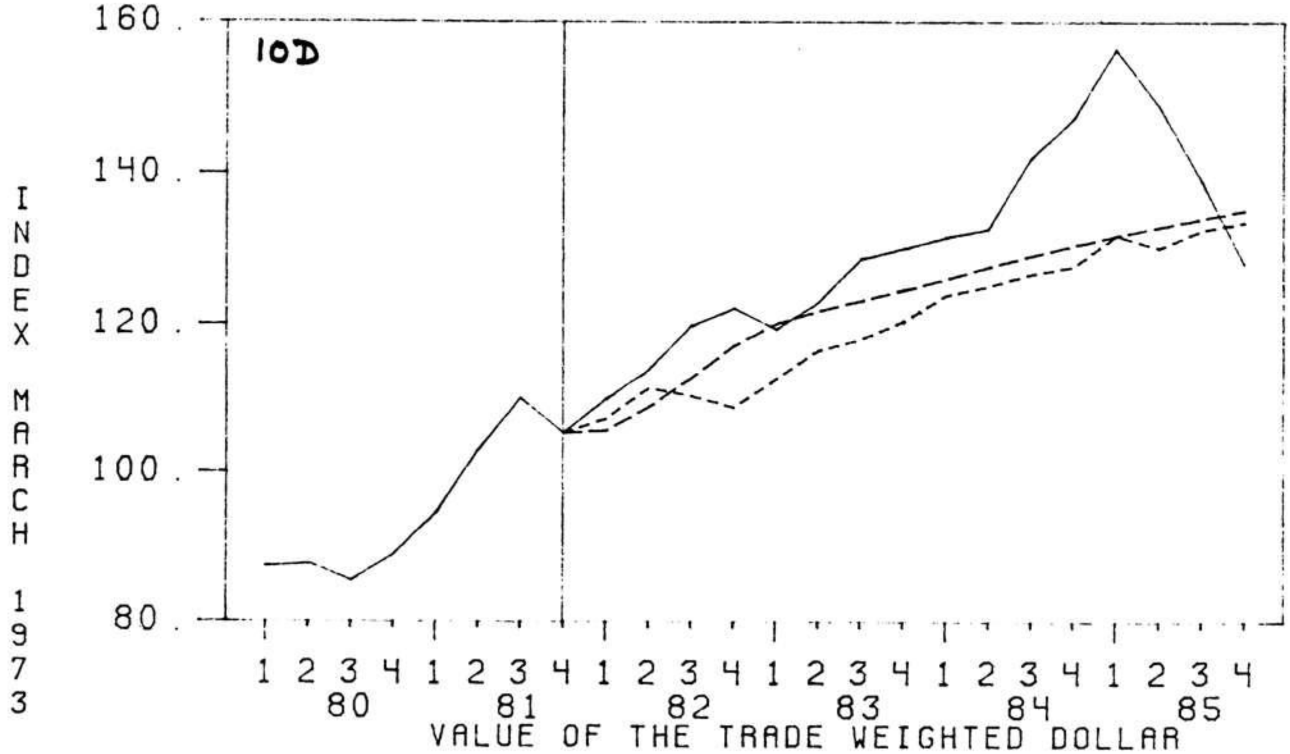




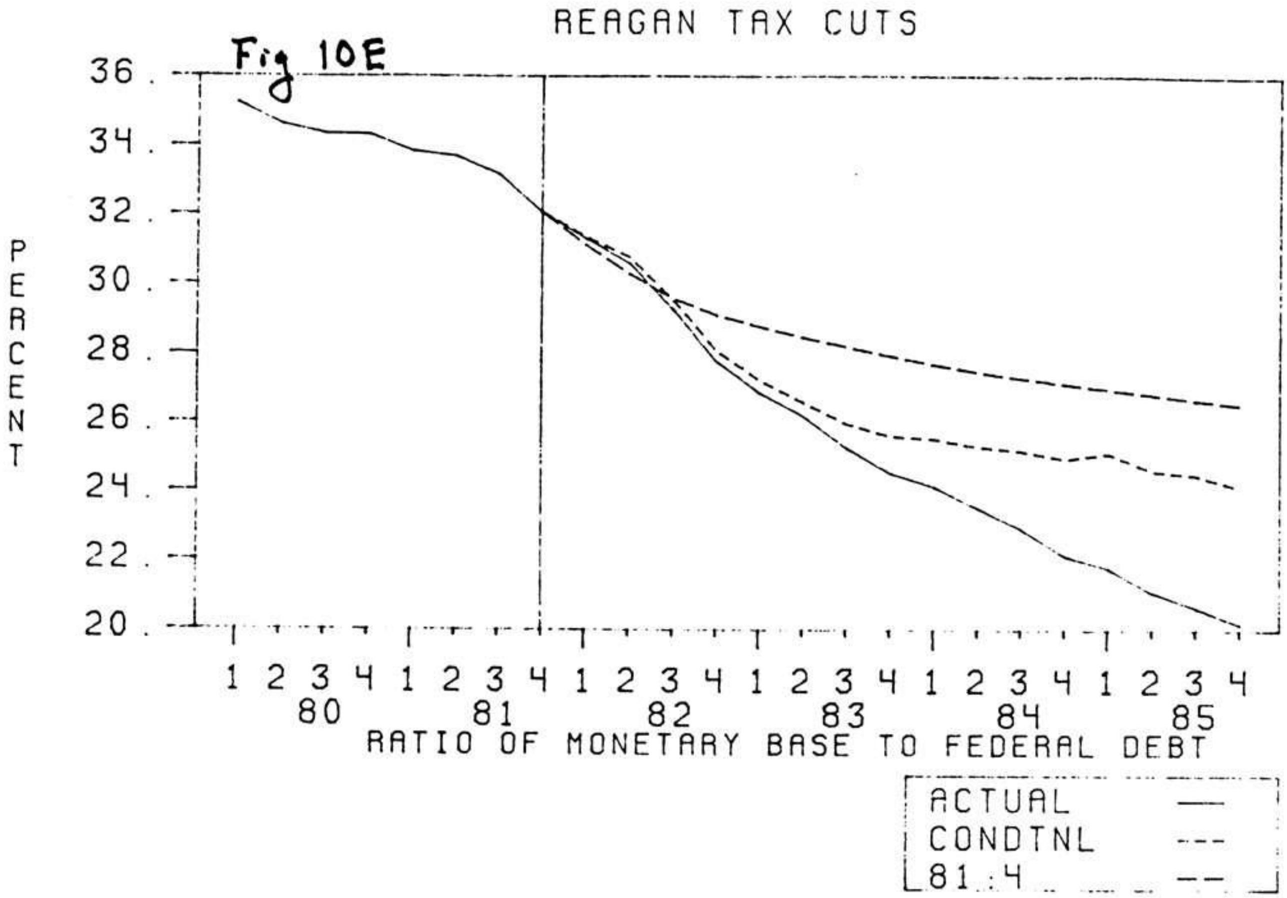
REAGAN TAX CUTS



3-MONTH TREASURY BILL RATE



VALUE OF THE TRADE WEIGHTED DOLLAR


REAGAN TAX CUTS
Fig 10E
36
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PERCENT
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84
85
RATIO OF MONETARY BASE TO FEDERAL DEBT
ACTUAL
CONDTNL
81:4