Recent U.S. Macroeconomic Stability: Good Luck, Good Policies, or Good Practices?

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Abstract: Several recent papers have noted a marked reduction in the volatility of many U.S. macroeconomic variables, both real and nominal, since somewhere around the early-to-mid 1980s. In particular, the variance of U.S. quarterly real GDP growth since 1984 is under half its level prevailing in the previous quarter-century. Three major possible explanations have been put forward, attributing the decline in volatility simply to "good luck", to "good macroeconomic policies" (in particular monetary policy), or to "good business practices" (especially better inventory management) enabled by recent strides made in the information technology sector. In this paper we develop a test that uses frequency domain techniques to distinguish the "good luck" hypothesis from the other two explanations. Additionally, we also estimate some VAR models over the two periods to see what can be learnt about the three hypotheses from these. Our frequency domain results lend considerable support to the "good luck" explanation, although there also appears to be something to the "good practices" hypothesis. The main result from the VAR work is that while the reduction in GDP growth volatility is primarily accounted for by a fall in the innovation variance, the reduction in inflation volatility can primarily be attributed to a change in structure. This is consistent with the "good luck" hypotheses as far as output variability is concerned, but appears to indicate a considerable role for policy, and perhaps practices, in taming inflation.

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1. Introduction

In light of the record duration of the most recent expansion that the U.S. economy has enjoyed, many analysts have focused on the possibility of a structural shift in the process driving output growth. Much of the work on comparing different periods has concentrated on examining changes in volatility across the pre- and post-war periods or on studying a downward shift in mean growth in the 1970s (the "productivity slowdown") and an upward shift in the mean growth in the 1990s (the "new economy").[1]

However, there has also been a marked reduction in output volatility since somewhere around the early-1980s–the U.S. economy has experienced only a single recession in almost two decades. This has been documented very recently by McConnel, Quiros, and Perez (1999) and McConnell and Perez (2000), who found that the variance of U.S. quarterly real GDP growth since 1984 has been less than half its value over the previous quarter century. Kim, Nelson, and Piger (2000) reach a similar conclusion, using Bayesian tests, although they find the reduction in volatility to be more broad-based than the other two studies did.

There is an on-going debate about the sources of the recent reduction in output volatility and whether it is concentrated in one or two components of output or is more widespread. There seem to be three leading possible explanations:

One hypothesis is that there has been a sharp drop in the variance of structural shocks hitting the U.S. economy over the past 15 years or so and, therefore, the reduction in volatility is simply a matter of "good luck". For example, Simon (2000) finds strong support for the good

[1]See, for example, the papers in the "Symposium on Business Cycles," *Journal of Economic Perspectives,* Spring 1999.

luck hypothesis, using a three-variable structural VAR approach with a long-run Blanchard-Quah style decomposition of shocks.

Another major explanation for the reduction in volatility centers around "good macroeconomic policies." In particular, it is often argued that better conduct of monetary policy in recent years has basically tamed the business cycle. A key contribution in this area is Clarida, Gali, and Gertler (2000). They provide evidence which indicates that the Federal Reserve appears to have acted much more aggressively to potential increases in inflation since the early 1980s. Moreover, simulations of their theoretical model of the economy demonstrate that a more aggressive stance of monetary policy is capable of stabilizing output to a considerable degree.

The third major explanation of the decline in the volatility of GDP growth appeals to changes in business practices, in large part brought about by rapid advances in information technology. McConnell et al. (1999) and Kahn et al. (2000) attribute a large part of the reduction in volatility to improvements in inventory management due to "just-in-time" computer based inventory management and ordering techniques in combination with better communication with the supply chain.[2]

One major goal of our paper is to provide a novel test of the "good luck" versus "good policies" and "good practices" hypotheses by using frequency domain techniques. The basic idea is to see if the reduction in volatility in various macroeconomic variables is concentrated at

[2]Other possible relevant change in practices may be the elimination of interest rate ceilings under Regulation Q which in tandem with the rise in a mortgage backed securities market helped generate a steadier supply of funds for housing investment, and thus stabilized residential investment. (See Ryding, 1990 and Throop, 1986). A third example of better practices might be the breakdown of trade barriers which may have allowed a smoother flow of goods across countries.

particular frequencies (e.g. the business cycle frequency) or is evenly distributed across frequencies. If it is evenly distributed, this would be pretty strong formal evidence of good luck being the leading explanation. Moreover, the techniques we employ avoid some of the well-known problems one confronts in the spectral domain, because we use estimates of the integrated spectrum over different frequency ranges, rather than estimates at particular frequencies. An added advantage of the frequency domain approach is that it can also speak to a possible fourth explanation for the decline in volatility, which is that it is a measurement issue; specifically, the Bureau of Economic Analysis may have managed to reduce the high frequency variability of real GDP, either through better construction of the NSA data or better seasonal adjustment.

Another objective of our paper is to extend the previous work on the explanations for the reduction in volatility in the time domain to a multivariate setting and examine the relative importance of "good luck," "good policies," and "good practices" in a VAR setting. This is very much in the spirit of Simon (2000), although given the particular relevance of the Lucas critique for these issues and given the critique of VARs that use recursive models only implicit in Faust (1998), we confine our conclusions, by and large, to what we can learn from the reduced form VARs. Specifically, we test for structural breaks in the coefficients of the reduced-form VARs as well as in the variances of the reduced-form errors. We also divide the reduction in volatility of the model variables into that due to changes in the variance of the predictable components and that due to changes in the variance of the one-step ahead forecast errors.

Our preliminary results are striking: First, like the papers mentioned above, we also find evidence for a structural break in volatility of real GDP growth around 1984. However, in contrast to McConnel and Perez (2000), we find that the structural break appears to extend to final sales growth as well, including durable final sales growth. Second, our frequency domain results indicate that for a broad range of supply side and demand side components of real GDP, we cannot reject the hypothesis that the reduction in variance has been evenly distributed at particular frequencies. This is quite strong support for the "good luck" hypothesis, although one major exception, durable goods final sales, also leaves open a significant role for better business practices as well. Finally, our VAR evidence indicates that for GDP growth, the reduction in the volatility of the innovations is in the same proportion as the reduction in the volatility of the variable itself. By contrast, for inflation, there is a large reduction in the volatility of the variable itself, but hardly any reduction in the volatility of its innovations. This suggests that while changes in the monetary policy reaction function, and perhaps better business practices also, may have a played big role in explaining more a more stable inflation since 1984 or so, these factors cannot account for much of the reduction in output volatility.

The remainder of the paper is organized as follows: Section 2 documents and characterizes the decline in the variance of output and its various demand and supply side components. In sections 3 and 4 we present and interpret evidence using frequency domain and VAR techniques, respectively. Section 5 concludes.

2. Documenting and Characterizing the Decline in Output Variance

Before discussing the causes of the shift in volatility, we detail the decline itself. Figure 1 graphs the annualized quarterly growth rates of GDP. It is immediately apparent that the swings in GDP growth have been much more muted in the past 15 years than in the previous period. This is true even if the very volatile period of 1980-83 shaded in gray is not considered.

This apparent discontinuity in the volatility of GDP growth has recently been confirmed using statistical methods. McConnell and Perez Quiros (2000) test for structural change in the mean and variance of GDP growth using a variety of techniques and find little evidence for a break in mean growth but statistically significant evidence of a variance break around 1984.[3] To date the exact break point between the two periods, they use GMM to jointly estimate a two equation model, consisting of an AR(1) process for GDP growth and an equation involving the absolute value of the residuals from the AR process. Their procedure rejects the null hypothesis that variance is equal across the sample and selects 1984:1 as the most likely breakpoint. Using an alternative Bayesian approach, Kim et al. (2000) also find a volatility break in real GDP growth at about the same time.

We verify these results using a test that allows for multiple breakpoints. Specifically, we construct the absolute value of GDP growth less its mean (AGDP) as a way of approximating the volatility of real GDP growth, and we test for multiple breaks in the mean of this series using an algorithm proposed by Bai and Perron (1998). We also test for a break in volatility by modeling GDP growth as an AR(4) process and applying the Bai-Perron test to the absolute value of the residuals. For the sample period from 1953:2 to 2000:1, we cannot reject the hypothesis that there is a single break and the test places the break at 1984:2.

In addition, for real GDP, we have also conduct two other tests: First, we estimate an AR model of the AGDP variable, allowing for a break point in the mean of the series. We use recursive OLS to estimate the model for different break dates and select the breakpoint that

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[3]The tests they use include a CUSUM and CUSUM of squares test and Nyblom's L test as described in Hansen (1992).

maximizes the F-statistic, determining its significance using bootstrapped critical values, as suggested by Diebold and Chen. Second, we use a MLE model of GDP growth that directly estimates the variance and uses similarly constructed critical values.[4]

Given the existence of a break in GDP volatility it is instructive to look more closely at the components of GDP to better characterize the break. Table 1 summarizes and extends work done by McConnell et al. (1999), McConnell and Quiros Perez (2000), and Kahn et al.(2000). The first two columns of the table show the standard deviation of the components of annualized quarterly GDP growth over the periods 1960:1 to 1983:4 and 1984:1 to 2000:1. The first row presents the standard deviation of overall GDP growth. The decline in volatility, already noted, is striking over the two periods: The standard deviation has more than halved–falling from 4.3 in the first period to 2.1 in the second. The next several rows present the variance of the broad demand components of GDP growth over the two periods. Volatility has declined notably across all major components, with the decline being the greatest in investment and exports and imports. Of the components of GDP, consumption growth shows one of the smallest declines in variance but, given its large share in GDP, it accounts for a good amount of the decline in volatility of overall GDP growth across the two periods. Figure 2 plots movements in the annualized growth rates of these demand components, where the changes in volatility are also apparent.

The second group of rows breaks down the volatility of GDP growth by its product components. Here, there appears to be more heterogeneity across components. The decline in the variance of GDP growth appears to be concentrated in goods and structures components, with

[4]We thank Norman Morin for programming these two tests. The exact timing of the date differs slightly depending on the lag length of the AR model.

little change in the volatility of services GDP across the two periods. The comparative stability of service volatility comes across plainly in the left side of figure 3, which shows the movements of the product side components of GDP.

The final two rows show the breakdown of real GDP growth into domestic final sales (which in nominal terms constitutes 99.5 percent of GDP) and the contribution of the change in private inventories to GDP growth. Final sales are further broken down into durable final sales and nondurable final sales. Table 1 and the right panel of figure 3 suggest that there have been large declines in the volatility of both final sales growth and the inventory contribution to GDP growth over the two periods. The decline in volatility is also evident in the nondurable and durable component of final sales. Overall, table 1 and figures 2 and 3 illustrate the broad-based nature of the decline in GDP volatility.

To support this ocular analysis, we also apply the Bai-Perron test to the variables listed in table 1, as well as to final sales of automobiles and two nominal variables, inflation and the federal funds rate, using quarterly data over the period 1953:2-2000:1, choosing the starting observation to be the same as in McConnel and Perez's work. The test results indicate one or two breaks occurring somewhere in the period 1979-84 in final sales growth, consumption growth, investment growth, goods GDP growth, structures GDP growth, inventories growth, inflation and the federal funds rate. For components of final sales, nondurable final sales growth and growth of automobile final sales display a structural break somewhere in the period 1986-88. These results are pretty similar whether the absolute values of the demeaned series themselves or the absolute value of the residuals from the AR(4) process are used. However, the result for durable final sales growth as well as inflation depends on which method is used. Taking just the absolute values of the demeaned series, three structural breaks are detected in durable final sales growth, 1961:1, 1977:4 and 1991:1. However, with the absolute values of the residuals from the AR model, two breaks are detected, one in 1986:2 and the other in 1988:1.

Thus, our results using the Bai-Perron test agree with McConell and Perez (2000) as to the behavior of aggregate real GDP, but appear to be in contrast to theirs when looking at components. Their tests indicated that the decline in volatility was concentrated mainly in durable goods inventories.

3. Testing the "Good Luck" Hypothesis in the Frequency Domain

Our motivation here is to test if the decline in volatility is concentrated more at particular frequencies or is more evenly distributed across frequencies. We do this by estimating the integrated spectrum over particular frequency ranges. Some background and our methodology is detailed below.

The spectrum of a series X_t is the Fourier transform of its covariogram and is given by:

$$h(\omega) = \sum_{j=-\infty}^{\infty} \Gamma(j) e^{-i\omega j}, \qquad -\pi < \omega < \pi \tag{1}$$

where $\Gamma(j)$ represents the jth lag population autocorrelation. Integrating the spectrum over the frequency range $-\pi$ to π gives the population variance of the series X.

The sample periodogram for a sample size of T is:

$$\hat{I}_T(\omega) \equiv \sum_{j=1-T}^{T-1} \hat{\Gamma}(j) e^{i\omega j} = \sum_{j=1-T}^{T-1} \hat{\Gamma}(j) \cos(\omega j) \tag{2}$$

where the $\hat{\Gamma}(j)$'s represent sample autocovariances given by:

$$\hat{\Gamma}(j) = \frac{1}{T}\sum_{t=1}^{T-j}(X_t - \overline{X})(X_{t-j} - \overline{X}) \tag{3}$$

The problems in using (2) as an estimate of the spectrum of X are well known. To try to address these problems, nonparametric estimates of the spectrum use Kernel estimation, but these can be very sensitive to the choice of kernel and band-width parameters. However, as Priestley (1982) shows, the estimates of the integrated spectrum are not subject to such severe problems and we use such estimates to test the "good luck" hypothesis.

The integrated spectrum over frequencies ω_1 to ω_2 is defined by:

$$H(\omega_1,\omega_2) \equiv \int_{\omega_1}^{\omega_2} h(\omega)d\omega \tag{4}$$

The integrated spectrum is equal to half the variance of the series accounted for by frequencies between ω_1 and ω_2. Consider the following estimate of the integrated spectrum over this frequency range:

$$\begin{aligned}\hat{H}_T(\omega_1,\omega_2) &\equiv \int_{\omega_1}^{\omega_2} \hat{I}_T(\omega)d\omega \\ &= \frac{\omega_2 - \omega_1}{2\pi}\hat{\Gamma}(0) + \frac{1}{\pi}\sum_{j=1}^{T-1}\hat{\Gamma}(j)\frac{[\sin(\omega_2 j) - \sin(\omega_1 j)]}{j}\end{aligned} \tag{5}$$

The second line follows from using (2) and the formula for the integral of a cosine function.

Priestley (p.474) establishes the following properties of $\hat{H}_T(\bullet)$:

Proposition:

$$\lim_{T\to\infty} E[\hat{H}_T(\omega_1,\omega_2) = H(\omega_1,\omega_2) \tag{6}$$

$$\lim_{T\to\infty} T\,\mathrm{var}[\hat{H}_T(\omega_1,\omega_2)] = 2\pi\int_{\omega_1}^{\omega_2} h^2(\phi)d\phi \equiv \Omega \tag{7}$$

Under reasonable regularity conditions, $\hat{I}_T(\omega)$ are asymptotically normally distributed and, hence:

$$\sqrt{T}[\hat{H}_T(\omega_1,\omega_2) - H(\omega_1,\omega_2) \to N(0,\Omega) \tag{8}$$

In order to apply these results from Priestley, we need to compute the variance of $\hat{H}_T(\omega_1,\omega_2)$, which equation (7) states is a consistent estimate of the variance of H. We show in the appendix that this is given by:

$$\hat{\Omega}_T = 2\pi\int_{\omega_1}^{\omega_2} \hat{I}_T^2(\phi)d\phi$$

$$= \frac{1}{T\pi}\times\left\{\begin{array}{l} \frac{1}{2}(\omega_2-\omega_1)\hat{\Gamma}(0)^2 + 2\hat{\Gamma}(0)\sum_{j=1}^{T-1}\hat{\Gamma}(j)\frac{[\sin(\omega_2 j)-\sin(\omega_1 j)]}{j} \\ +\sum_{j=1}^{T-1}\hat{\Gamma}(j)^2 + \left[(\omega_2-\omega_1)+\frac{1}{2}\frac{\sin(2\omega_2 j)-\sin(2\omega_1 j)}{j}\right] \\ +2\sum_{j=1}^{T-1}\sum_{k=j+1}^{T-1}\hat{\Gamma}(j)\hat{\Gamma}(k)\left[\begin{array}{l}\frac{\sin(\omega_2(j+k))-\sin(\omega_1(j+k))}{j+k} \\ +\frac{\sin(\omega_2(k-j))-\sin(\omega_1(k-j))}{k-j}\end{array}\right]\end{array}\right\} \tag{9}$$

Now we can describe our methodology of testing the "good luck" hypothesis in the frequency domain. We choose three ranges of frequencies, which we label low frequencies, business cycle frequencies, and high frequencies. We estimate $\hat{H}_T(\omega_1, \omega_2)$, using (5) and the standard error for each of these ranges, using (9), separately for each of the two subperiods. We then can see what the variance accounted for by particular frequency ranges is in each of our sample periods and whether it is statistically significant. We also compute the test statistic $\Delta\hat{H}(\bullet) / s.e.[\Delta\hat{H}(\bullet)]$, where $\Delta\hat{H}(\bullet) = \hat{H}_{T_1}(\bullet) - \hat{H}_{T_2}(\bullet)$, for each of the frequency ranges, and where T_1 , T_2 refer to the number of observations in the first and second periods, respectively. This allows us to test if the variances at different frequency ranges are significantly lower in the second period.

If the variances in the second period are lower at different frequency ranges, the key question for the good luck hypothesis is whether they have fallen proportionately over all frequency ranges or disproportionately at some frequencies. To test this we normalize the integrated spectrum so that over frequencies 0 to π, its value is 0.5, or equivalently over frequencies $-\pi$ to π its value is 1. Twice the normalized integrated spectrum over a particular frequency range then gives us the proportion of the variance accounted for by that frequency range. More specifically, the integrated normalized spectrum is defined as:

$$\hat{G}_T(\omega_1, \omega_2) = \hat{H}_T(\omega_1, \omega_2) / \hat{\Gamma}(0) \tag{10}$$

Clearly, the variance of the integrated normalized spectrum in (10) is given by:

$$\text{var}[\hat{G}_T(\omega_1, \omega_2)] = \text{var}[\hat{H}_T(\omega_1, \omega_2)] / \hat{\Gamma}(0)^2 \tag{11}$$

The implication of the "good luck" hypothesis that the variance has fallen proportionately at all frequency ranges can then be tested by seeing if $\hat{G}_{T_1}(\bullet)$ is statistically different from $\hat{G}_{T_2}(\bullet)$ over particular frequencies. If the $\hat{H}(\bullet)$'s are lower in the second period but the $\hat{G}(\bullet)$'s are the same over each of our three frequency ranges, we cannot reject the "good luck" explanation.

Results

Tables 2 and 3 present our results from the estimation of the integrated spectrum and the integrated normalized spectrum. The three frequency ranges we use are Low frequencies (0 to $\pi/16$), business cycle (broad) frequencies ($\pi/16$ to $\pi/3$)—labeled BCB in the tables—and high frequencies ($\pi/3$ to π). The broad range for the business cycle frequency is taken from Baxter and King (1995) and corresponds in periods to cycles of 6 to 32 quarters. We also computed a narrow range for the business cycle frequency, corresponding to Sargent (1979)'s definition of frequencies $\pi/8$ to $\pi/4$, corresponding to cycles of 8 to 16 quarters; the results were largely similar and cases of significant differences are noted in the text.

The first column in table 2 reports twice the estimate of the integrated spectrum in particular frequency ranges over the first sample, together with its standard error in paranhesis. The second column reports the same thing from the second sample. The third column gives the test statistic of for whether the integrated spectrum is different across the two periods, and the last column reports the marginal significance level for a two-tailed test corresponding to this null hypothesis.

We report results for aggregate real GDP and several demand side and supply side components of it. The latest 1996 chain-weighted data are used in the computation of all the statistics. In each case it is assumed that a structural break occurs around the start of 1984, corresponding to the period where most of the literature seems to place the structural break in GDP volatility. For almost all cases, the first sample period is 1960:1 to 1979:4 and the second sample period runs from 1984:1 to 2000:1. (The exception is inventories where we could find 1996 chain-weighted data only from 1967:1).

Note that the period 1980-83 is omitted. There are several reasons for this. First, the Bai and Perron test we use does not always indicate a structural break exactly at 1984 for each of the series; however generally it falls in the 1979-1984 range. Second, it is generally believed that the monetary policy rule being followed was quite different in the 1979-84 period from the other two periods and, therefore, this period may have been different from each of the other two periods. Finally, omitting some observations from the middle should lend more power to our tests for detecting differences across the subsamples.[5]

Let's consider the results in table 2 for aggregate real GDP. The low frequency, the business cycle frequency, and the high frequency rows sum to the sample variance of real GDP growth. Thus the first two columns for the GDP growth variable show that the variance has fallen from about 16 to about 4.5 from the first to the second period. Also, the variance is concentrated at the business cycle and high frequencies, where it is significantly different from zero in each case for each period. The business cycle frequency variance is 7 in the first period and 1.5 in the second period. Looking at the differences between the two periods, we can see

[5]In some cases, e.g. nondurable final sales, durable final sales, and exports and imports a a structural break outside of the 1979-84 range was found. In such cases, we have also estimated the integrated and integrated normalized spectra for those series using that break date.

from the third column that the variance at the business cycle and higher frequencies in the first period is significantly higher compared to the second period.

The above results for aggregate GDP carry over for the most part to the demand side components of GDP, using a 10 percent level of significance, or alternatively using a 5 percent level of significance and a one-tailed test. A one-tailed is probably better, since it seems more appropriate to have as the alternative hypothesis that the variance in the second period is lower, rather than it is either higher or lower. The main exception is imports, which only shows a statistically significant decline in the variance at the high frequencies. Additionally, if the narrow business cycle frequencies are used, the decline in variance in investment growth in the second period at the business cycle frequencies turns out to be not statistically significant.

Turning to the product side components, goods GDP growth and structures GDP growth also show also show a decline in variance at the business cycle frequencies and high frequencies. For structures, this result is overturned for the business cycle frequencies, if the narrower band is used. For services, however, there appears to be no significant change in the variance at any of the frequency ranges, which seems consistent with our ocular examination of the data in figure 3.

Table 2 also reports results for final sales and some of its components. Interestingly, final sales growth exhibits a statistically significant decline in variance at the business cycle frequencies, but not at high frequencies. The same holds for durable final sales, unless the narrower business cycle frequency range is used. Nondurable final sales growth exhibits a decline in variance in the second period only if a one-tailed test is used. Automobile final sales are characterized by a decline in variance both at the business cycle frequencies and higher frequencies as well, if a one-tailed test is used.

For completeness, we have also included some nominal variables in our frequency domain analysis, since these variables go into our VAR estimates to be presented in the next section. From table 2, the main noteworthy feature from these results is the statistically significant decline in the high frequency variance of the federal funds rate.

Now consider the results from estimation of the integrated normalized spectrum, which are reported in table 3. The rows correspond to the proportion of variance accounted for by various frequency ranges and the sum for the three rows should, therefore, be unity.

The results on aggregate real GDP growth show that the variance is concentrated at the business cycle and higher frequencies, with roughly an equal division between the cycle and the high frequency band. This is also true of consumption, but the proportion of variance accounted for by high frequencies increases as we move to investment and especially to trade. Production side components also have the variance concentrated at the business cycle and higher frequencies, with the important exception that one third of the variance for services GDP growth is accounted for by the low frequencies. As for sales, most of the variance is at the high frequencies, but business cycle frequencies also account for a substantial proportion. These results are fairly consistent across the two periods.

As to differences across the two periods, these results are easy to summarize for the real variables, as they are very consistent across different components. For any of the frequency ranges, it is only in the case of durable final sales growth using a one-tailed test, that we can find any evidence that the proportion of variance accounted for by the chosen frequency range is different across the two periods. This is quite a remarkable result especially given that table 2 shows that our method is, in principle, capable of picking up any differences that exist across the periods.

Our results imply that we cannot reject the hypothesis that the decline in output variability is evenly distributed across frequencies (at least across business cycle and higher frequencies), rather than being concentrated at particular frequencies. This is consistent with the hypothesis that the fall in volatility can largely be accounted for by decline in the variance of structural disturbances hitting the economy and any change in structure has only made marginal contributions to the decline in volatility. For durable goods the decline in volatility is concentrated at the business cycle frequency, which appears to imply that practices may have played some role too. To a substantial degree, though, we take this evidence to be in agreement with the "good luck" hypothesis. Practices and policy could have played a larger role, but it would be through affecting the shocks rather than the structure of the economy, e.g.. less erratic monetary policy. Strictly speaking, we do not find any decline in volatility at the low frequencies in the first place in table 2; however for the lower frequencies we never found anything to be significant and there might be power considerations involved here.

To complete the discussion of the results for the integrated normalized spectrum, we should note that for the nominal variables, the proportion of variance accounted for by high frequencies has gone down statistically significantly for the federal funds rate, but gone up statistically significantly for inflation from the first to the second periods.

4. VAR Results

In this section, we extend some of the work that has been done in the time domain to a multivariate setting. Specifically, we consider what can be learnt about delineating the role played by good luck, good practices, and good policy from estimation of a VAR model. This provides one simple way to study how important changes in propagation and dynamic interactions between variables have been in reducing volatility and how important reductions in the volatility of the shocks themselves have been.

In a very recent paper, Simon (2000) also estimates a VAR to study the issue of the reduction in volatility. Our work is in the same spirit, but differs from his in several respects. First, his model has somewhat different variables from our basic model. Second, we are interested in extending the basic VAR model to distinguish between final sales and inventories and also compare results with monthly and quarterly data, since such issues pertain to distinguishing between the "better business practices" explanation from the other two explanations. Third, Simon makes very strong identification assumptions and some of his important conclusions are dependent on his identified structural VAR and are subject to the Lucas critique.

Because of the importance of the Lucas critique for these issues and given that Faust (1998) has shown that conclusions from identified VARs using recursive models may not be very robust[6], we try to restrict our attention to conclusions from the estimated reduced-form VAR

[6]More specifically, Faust shows that recursive identifications are not the only ones that give qualitatively plausible effects of, say, the effect of monetary policy shocks on the economy. Moreover, when a search is done over all possible identifications with plausible looking effects of monetary policy shocks, one gets a wide range of results on how much of the output variance money shocks explain, for example.

as much as possible, although we do summarize some results from structural VARs with a warning that they should be taken with a pinch of salt.

Our basic VAR model is in the spirit of small-scale VAR models as Sims (1980), Christiano, Eichenbaum, and Evans (1998). Leeper, Sims and Zha (1996) also discuss such VAR models, among others. Specifically, our VAR consists of the following four variables: output growth, consumer price inflation, commodity price inflation, and the federal funds rate. The volatility of output growth and inflation are of direct interest, and the federal funds rate is included as the policy variable.[7] Commodity price inflation is included for the usual reason that it might proxy for information about expected future inflation that is not available in the history of other variables and, therefore, help to mitigate the price puzzle that typically appears in these types of VAR models. Two other VAR systems are also estimated. One that distinguishes between final sales and inventories and one that estimates the basic model using monthly data.

Tables 4 and 5 report some basic statistics on the six variables that go into the two VARs that use quarterly data described above for two subperiods. Note that we drop the period from 1980-83 for reasons that have been already discussed. The real variables have also already been described earlier. For the nominal variables, we use the aggregate consumer price index to compute CPI inflation. Our commodity price index is the PPI index for crude materials, which quite closely tracks the index of sensitive materials that the CEE and other models have used in

[7]Note, however, that Leeper et al. (1996) have argued that a single short-term interest rate is unlikely to adequately capture monetary policy. According to them to have hope of adequately capturing policy responses, one needs to model a dynamic system with several monetary aggregates and perhaps multiple interest rates.

the past, but is more up to date. The federal funds rate used as our monetary policy variable is computed as a quarterly average of monthly data for the quarterly model.

Table 4 shows that the mean growth rate of real GDP is not that much different between the pre-1980 and post-1983 periods. This indicates that the hypothesis of a mean break in GDP growth appears to be less distinctive feature of the data than it used to be until a few years ago, which is also consistent with the McConnel and Perez (2000) results. However, there has been a significant decline in the mean of the inflation rate and a dramatic decline in the mean of commodity price inflation in the second period. Notice that the mean value of the federal funds rate went up slightly in the second period.

Our primary interest here is in differences in volatility of these variables, which are shown in table 5. The standard deviation of real GDP growth, which has halved in the post-1983 period to about 2 percent from about 4 percent in the pre-1980 period, has already been discussed, as have final sales growth and inventories growth. But note that the volatility of inflation is also dramatically less in the second period. Interestingly, the volatility of commodity price has not decreased in the post-83 period.

Results from the 4-variable VAR

We first estimate the reduced-form 4-variable VAR separately over the two periods, 1960:1-1979:4 and 1984:1-2000:1, and then conduct Goldfeld-Quandt tests of constancy of error variances and Chow tests of regression coefficient stability. A dummy variable for 1986:2 is included as this dramatically improved the fit of the inflation equation over the second period.

The results are shown in table 6. Notice that only the inflation equation appears to display coefficient instability across the two periods. However, once we impose 0 restrictions that cannot be rejected across both sample periods, the GDP growth equation and federal funds rate equation also display coefficient instability. For the error variances, the reduced form innovations to the growth equation and the federal funds rate equation display much less volatility in the second period, while those of the inflation equation and the commodity price equation have similar volatility across periods. In principle, it seems so far that both changes in structure and changes in innovation variance could account for the reduction in overall volatility of the variables considered.

To study this further, we decompose the variance of the variables for each period into the variance of the fitted (predictable) component of the reduced-form equation and the variance of the innovation. The results reported in table 6 are striking. The innovation variance of the GDP growth equation falls by the same proportion as the fall in variance of growth itself. However, in the case of inflation, the innovation variance hardly changes at all, but there is a dramatic drop in the variance of the predictable component. This is also evident in figures 4 and 5. Notice from figures 6 and 7 that the reduction in the volatility of the federal funds rate is concentrated in both the predictable component and the innovation variance, while for commodity price inflation there has not been much reduction in volatility in either component.[8]

The above results make it seem unlikely that changes in the coefficients of the monetary policy reaction function or changes in other coefficients due to better business practices are causing the reduction in volatility of real GDP growth since the mid-1980s. However, to the

[8] In figure 7, the large negative shock in 1984Q3 in the federal funds rate probably has to do with the technical details of Federal Reserve policy targeting borrowed reserves following the Continental Illinois failure.

extent that the decreased variance of reduced-form innovations to real GDP growth are themselves a result of less erratic monetary policy or smoother business practices, then these things might matter.[9] In any case, as for the reduction in inflation volatility--which is concentrated almost entirely in the predictable component--it seems very likely that the inflation rate is better behaved because people have come to expect better policy from the Federal Reserve. Thus, it is in taming inflation, rather than in taming the business cycle that policy should be given credit, although changes in business practices may have played a role here too.

Results from other VAR systems

To study the role of business practices further it would be interesting to see if the above results on real GDP growth go through and apply to final sales as well in a system that distinguishes between final sales and inventories. The motivation for this is that perhaps part of the result of better inventory management is less shocks to inventories, and these shocks account for the bulk of the reduction in the innovation variance of real GDP growth. Another possibility is that because we use quarterly data, what are structural changes at the monthly frequency might be getting labeled as shocks at the quarterly frequency, not giving enough credit to business practices and perhaps policy as well.

Due to these two possibilities we also estimate a 5-variable quarterly model that replaces GDP by final sales and inventories as well as a 4-variable monthly model that replaces real GDP growth by industrial production growth. When estimating the 5-variable model, account should

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[9]Note, though, that Leeper et al. (1996) argue that most variation in monetary policy is accounted for by responses of the monetary authority to the state of the economy, rather than by random disturbances to policy behavior.

be taken of the strong likelihood that inventories and final sales are cointegrated and, therefore, for this model we include an error-correction term representing the logarithm of the ratio of inventories to final sales in each equation.

The results for the 5-variable model are reported in table 7. Note that the coefficients of the final sales equation display instability, while those of the inventories equation do not. Both innovation variances are statistically significantly lower, however. Once again, the reduction in final sales innovation variance is in about the same proportion as the reduction in the predictable component variance. The monthly model reported in table 8 also gives similar results. The innovation variances for the output and federal funds rate equation are significantly lower in the second period. Additionally, variance of the output error term falls in about the same proportion as the variance of output growth itself and this is not the case for inflation.

Structural VAR Results

We have also estimated alternative recursive structural models for our 4-variable system, placing both the federal funds rate variable last as well as first in the ordering, since both choices are around in the literature. Two main themes, which are consistent with the reduced-form results, emerge. First, no matter how the variables are ordered, it is the structural output innovation and the structural federal funds rate innovation which display the reduction in variance. Thus, the importance of good luck cannot be attributed to more favorable commodity prices or more favorable shocks to inflation that are uncorrelated with the output and federal funds rate shocks. Second, if we do certain counterfactuals, such as taking the coefficients of the estimated policy reaction function from one period and putting them in the other period with the other coefficients unchanged, this does not change the unconditional variances much. The same is true of the coefficients of the GDP equation, although switching the coefficients of the inflation equation does have some effect. By contrast if the innovation variances are switched across the two periods, without a change in structure, there are substantial changes in the unconditional variance of output growth.

While we have mentioned these results, it is unclear how much stock one should place in them given the severity of the Lucas critique in this context and the lack of robustness of conclusions from VAR models with a small number of variables.

5. Concluding Remarks

In this paper we have attempted to provide a novel test of the “good luck” explanation of the reduction in U.S. output volatility over the last 15-20 years, using frequency domain techniques. We have considered several real variables, including aggregate output and its various demand side and production side components. Our results do not lend much support to the hypothesis that the reduction in variance has been concentrated at the business cycle frequencies, with the exception of durable goods. For all other variables, we cannot reject the hypothesis that the decline in variance has been evenly distributed at the various frequencies. This lends considerable support to the “good luck” explanation, as in the time-series work of Simon (2000), although the durable goods results are consistent with some role for “good practices” as well.

Our reduced-form VAR estimates indicate that the reduction in aggregate output growth volatility is primarily accounted for by a fall in the innovation variance. However, the reduction in inflation volatility is primarily accounted for by a change in structure. These results are not changed if we use final sales instead of real GDP in our quarterly model, thereby distinguishing between innovations to inventories and innovations to final sales, or if we use monthly data. Again these results are consistent with the hypothesis that, as far as output volatility, is concerned it appears that the reduction in variance of structural innovations would account for it, rather than a change in economic structure. It is not that we do not find any changes in structure–most of the reduced-form equations display coefficient instability across the two periods. It is just that this change in structure does not appear to account for much of the reduction in volatility.

However, when it comes to inflation, changes in structure do account for the reduction in volatility, as opposed to a reduction in innovation variance. This is consistent with policy, and perhaps also practices, playing a major role in leading to more stable behavior for inflation.

The results suggest that at least as far as output variability is concerned, it might be premature to pat ourselves on the back and regard the reduction in volatility to be a permanent feature of the U.S. economy.

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Table 1: Volatility of Growth in Real GDP and its Components

Standard deviations of Annualized Quarterly Growth Rates

	Standard Deviation I:1960-1983	Standard Deviation II:1984-1999	Difference (II-I)	Share in Nominal GDP (pct.)
GDP	4.32	2.13	-2.19	100
Demand Components				
Consumption	3.34	2.15	-1.19	67.6
Investment	21.94	12.59	-9.35	17.5
Government	4.39	3.64	.75	6.2
Exports	18.71	7.29	-11.42	10.8
Imports	17.87	7.58	-10.29	13.5
Product Components				
Goods	7.78	4.35	-3.43	37.6
Structures	11.80	6.83	-4.97	9.1
Services	1.71	1.39	-.32	53.3
Other				
Final Sales	3.38	2.11	-1.27	99.5
Final Sales of Durables	9.68	8.17	-1.51	
Final Sales of Nondurables	4.33	2.94	-1.39	
Change in Pvt. Inventories*	2.73	1.71	-1.02	.5

* Contribution to GDP Growth

Table 2: Estimates of Integrated Spectrum

Variable & Frequency	$2\hat{H}_{T_1}(\omega_1,\omega_2)$	$2\hat{H}_{T_2}(\omega_1,\omega_2)$	$\frac{2\Delta\hat{H}(\bullet)}{\text{s.e}[2\Delta\hat{H}(\bullet)]}$	Marginal Significance Level
Real GDP Growth:				
Low	0.93 (.70)	0.84 (.77)	0.09	.93
BCB	7.08 (2.50)	1.54 (.69)	2.13	.03
High	7.64 (2.00)	2.10 (.62)	2.64	.00
Consumption Growth:				
Low	0.66 (.48)	1.02 (.94)	-0.34	.73
BCB	3.86 (1.59)	1.07 (.53)	1.67	.09
High	4.90 (1.35)	2.45 (.78)	1.58	.11
Investment Growth:				
Low	4.60 (4.27)	14.90 (13.07)	-0.75	.45
BCB	157.54 (56.56)	46.94 (22.16)	1.79	.07
High	241.01 (64.30)	92.18 (25.19)	2.16	.03
Export Growth:				
Low	3.25 (2.55)	3.10 (3.10)	0.04	.97
BCB	59.37 (23.14)	16.49 (7.87)	1.75	.08
High	324.53 (82.85)	32.80 (11.59)	3.49	.00
Import Growth:				
Low	7.77 (6.21)	9.62 (8.55)	-0.95	.34
BCB	74.46 (27.82)	12.85 (5.82)	0.097	.92
High	227.58 (60.03)	34.09 (9.05)	3.19	.00

NOTES:
1. Standard errors in parantheses.
2. Low freq. range = 0,π/16; BCB = Bus. cycle broad freq. range = π/16,π/3; High freq. range = π/3,π.
3. $\Delta\hat{H}(\bullet) = \hat{H}_{T_1}(\omega_1,\omega_2) - \hat{H}_{T_2}(\omega_1,\omega_2)$.
4. T_1 and T_2 refer to period 1 (1960:1-1979:4) and period 2 (1984:1-2000:1), respectively. For inventories growth, however, period 1 begins in 1967:2.
5. Marginal significance level is for two-tailed test; for a one-tailed test it should be halved.

Table 2 (continued): Estimates of Integrated Spectrum

Variable & Frequency	$2\hat{H}_{T_1}(\omega_1,\omega_2)$	$2\hat{H}_{T_2}(\omega_1,\omega_2)$	$\frac{2\Delta\hat{H}(\bullet)}{\text{s.e}[2\Delta\hat{H}(\bullet)]}$	Marginal Significance Level
<u>Goods GDP Growth:</u>				
Low	1.55 (1.21)	1.76 (1.52)	-0.11	.91
BCB	18.08 (6.66)	4.95 (2.27)	1.87	.06
High	30.99 (7.72)	11.96 (3.51)	2.24	.03
<u>Structures GDP Growth:</u>				
Low	5.43 (4.79)	8.66 (7.53)	-0.36	.72
BCB	50.33 (18.78)	17.58 (8.41)	1.59	.11
High	58.72 (15.50)	19.70 (5.38)	2.38	.02
<u>Services GDP Growth:</u>				
Low	0.68 (.56)	0.49 (0.43)	0.28	.78
BCB	0.44 (.17)	0.33 (0.14)	0.47	.64
High	1.45 (.39)	1.09 (0.34)	0.71	.48

Table 2 (continued): Estimates of Integrated Spectrum

Variable & Frequency	$2\hat{H}_{T_1}(\omega_1,\omega_2)$	$2\hat{H}_{T_2}(\omega_1,\omega_2)$	$\frac{2\Delta\hat{H}(\bullet)}{s.e[2\Delta\hat{H}(\bullet)]}$	Marginal Significance Level
Final Sales Growth:				
Low	0.82 (.64)	0.90 (.82)	-0.07	.94
BCB	4.56 (1.58)	0.93 (.43)	2.14	.03
High	4.48 (1.17)	2.55 (.82)	1.35	.18
Dur. Final Sales Growth:				
Low	3.06 (2.50)	6.00 (5.04)	-0.52	.60
BCB	29.43 (10.86)	7.73 (3.53)	1.90	.06
High	45.28 (12.27)	51.98 (16.10)	-0.33	.74
Nondur. Final Sales Gr.				
Low	0.78 (.68)	0.40 (.37)	0.48	.63
BCB	4.93 (1.88)	1.74 (.82)	1.56	.12
High	12.18 (3.42)	6.38 (2.10)	1.45	.15
Auto Final Sales Gr.				
Low	33.8 (27.30)	10.67 (8.67)	0.81	.42
BCB	395.1 (141.71)	54.30 (23.48)	2.37	.02
High	1172 (330.37)	526.11 (148.9)	1.78	.08
Inventories Growth:				
Low	0.19 (.18)	1.02 (.93)	-0.88	.38
BCB	5.97 (2.94)	4.22 (2.02)	0.49	.62
High	3.91 (1.27)	2.59 (.79)	0.88	.38

Table 2 (continued): Estimates of Integrated Spectrum

Variable & Frequency	$2\hat{H}_{T_1}(\omega_1,\omega_2)$	$2\hat{H}_{T_2}(\omega_1,\omega_2)$	$\frac{2\Delta\hat{H}(\bullet)}{\text{s.e}[2\Delta\hat{H}(\bullet)]}$	Marginal Significance Level
Inflation:				
Low	6.70 (6.41)	0.59 (.48)	0.95	.34
BCB	3.59 (2.08)	0.82 (.38)	1.31	.19
High	0.98 (.29)	0.65 (.19)	0.97	.33
Federal Funds Rate:				
Low	3.03 (2.73)	2.10 (1.89)	0.28	.78
BCB	3.35 (1.98)	1.71 (1.17)	0.71	.47
High	0.45 (.14)	0.09 (0.04)	2.52	.01
Comm. Price Inflation:				
Low	21.25 (17.37)	3.10 (2.88)	1.03	.30
BCB	67.19 (25.55)	92.96 (40.36)	-0.15	.88
High	88.71 (21.53)	128.18 (43.50)	-0.82	.41

Table 2: Estimates of Normalized Integrated Spectrum

Variable & Frequency	$2\hat{G}_{T_1}(\omega_1,\omega_2)$	$2\hat{G}_{T_2}(\omega_1,\omega_2)$	$\frac{2\Delta\hat{G}(\bullet)}{s.e[2\Delta\hat{G}(\bullet)]}$	Marginal Significance Level
Real GDP Growth:				
Low	.06 (.05)	.19 (.17)	-.72	.47
BCB	.45 (.16)	.34 (.15)	.49	.62
High	.49 (.13)	.47 (.14)	.10	.92
Consumption Growth:				
Low	.07 (.05)	.22 (.21)	-.72	.47
BCB	.41 (.17)	.24 (.12)	.85	.40
High	.52 (.14)	.54 (.17)	-.09	.93
Investment Growth:				
Low	.01 (.01)	.10 (.08)	-1.00	.32
BCB	.39 (.14)	.31 (.14)	.38	.70
High	.60 (.16)	.59 (.16)	.31	.97
Export Growth:				
Low	.01 (.01)	.06 (.06)	-.86	.39
BCB	.15 (.06)	.31 (.15)	-.99	.32
High	.84 (.21)	.63 (.22)	.69	.49
Import Growth:				
Low	.03 (.02)	.17 (.15)	-.95	.34
BCB	.24 (.09)	.23 (.10)	.10	.92
High	.73 (.19)	.60 (.16)	.52	.60

NOTES:

1. Standard errors in parantheses.
2. Low freq. range = 0,π/16; BCB = Bus. cycle broad freq. range = π/16,π/3; High freq. range = π/3,π.
3. $\Delta\hat{G}(\bullet) = \hat{G}_{T_1}(\omega_1,\omega_2) - \hat{G}_{T_2}(\omega_1,\omega_2)$.
4. T_1 and T_2 refer to period 1 (1960:1-1979:4) and period 2 (1984:1-2000:1), respectively. For inventories growth, however, period 1 begins in 1967:2.
5. Marginal significance level is for two-tailed test; for a one-tailed test it should be halved.

Table 3 (continued): Estimates of Normalized Integrated Spectrum

Variable & Frequency	$2\hat{G}_{T_1}(\omega_1,\omega_2)$	$2\hat{G}_{T_2}(\omega_1,\omega_2)$	$\frac{2\Delta\hat{G}(\bullet)}{\text{s.e}[2\Delta\hat{G}(\bullet)]}$	Marginal Significance Level
Goods GDP Growth:				
Low	.03 (.02)	.09 (.08)	-.75	.45
BCB	.36 (.13)	.27 (.12)	.51	.61
High	.61 (.15)	.64 (.19)	-.12	.90
Structures GDP Growth:				
Low	.05 (.05)	.19 (.16)	-.83	.41
BCB	.44 (.16)	.38 (.18)	.23	.82
High	.52 (.14)	.43 (.12)	.47	.64
Services GDP Growth:				
Low	.26 (.22)	.26 (.23)	.03	.98
BCB	.17 (.07)	.17 (.08)	-.35	.97
High	.56 (.15)	.57 (.18)	-.24	.98

Table 3 (continued): Estimates of Normalized Integrated Spectrum

Variable & Frequency	$2\hat{G}_{T_1}(\omega_1,\omega_2)$	$2\hat{G}_{T_2}(\omega_1,\omega_2)$	$\frac{2\Delta\hat{G}(\bullet)}{\text{s.e}[2\Delta\hat{G}(\bullet)]}$	Marginal Significance Level
Final Sales Growth:				
Low	.09 (.07)	.21 (.19)	-.61	.54
BCB	.45 (.16)	.21 (.10)	1.28	.20
High	.46 (.12)	.58 (.19)	-.55	.58
Dur. Final Sales Growth:				
Low	.04 (.03)	.09 (.08)	-.63	.53
BCB	.38 (.14)	.12 (.05)	1.74	.08
High	.58 (.16)	.79 (.24)	-.72	.47
Nondur. Final Sales Gr.				
Low	.04 (.04)	.05 (.04)	-.06	.95
BCB	.28 (.11)	.20 (.09)	.50	.62
High	.68 (.19)	.75 (.25)	-.22	.83
Auto Final Sales Gr.				
Low	.02 (.02)	.02 (.02)	.14	.89
BCB	.25 (.09)	.09 (.04)	1.60	.11
High	.73 (.21)	.89 (.25)	-.49	.62
Inventories Growth:				
Low	.02 (.02)	.13 (.12)	-.93	.35
BCB	.59 (.29)	.54 (.26)	.14	.89
High	.39 (.13)	.33 (.10)	.36	.72

Table 3 (continued): Estimates of Normalized Integrated Spectrum

Variable & Frequency	$2\hat{G}_{T_1}(\omega_1,\omega_2)$	$2\hat{G}_{T_2}(\omega_1,\omega_2)$	$\frac{2\Delta\hat{G}(\bullet)}{\text{s.e}[2\Delta\hat{G}(\bullet)]}$	Marginal Significance Level
Inflation:				
Low	.59 (.57)	.29 (.24)	.50	.62
BCB	.32 (.18)	.40 (.18)	-.31	.76
High	.09 (.03)	.31 (.09)	-2.39	.02
Federal Funds Rate:				
Low	.44 (.40)	.54 (.48)	-.15	.88
BCB	.49 (.29)	.44 (.30)	.13	.90
High	.07 (.02)	.02 (.01)	1.93	.05
Comm. Price Inflation:				
Low	.12 (.10)	.01 (.01)	1.07	.28
BCB	.38 (.14)	.41 (.18)	-.15	.88
High	.50 (.12)	.57 (.19)	-.31	.76

Table 4: Mean of Model Variables

Means of Annualized Quarterly Growth Rates

	Mean		Difference
	I:60:1-79:4	II:84:1-00:1	(II-I)
GDP	3.74	3.38	-.36
CPI Inflation	4.76	3.20	-1.56
Commodity Price Inflation	5.41	.46	-4.95
Federal Funds Rate (level)	5.64	6.24	.60
Final Sales	3.75	3.37	-.38
Inventories	4.10	3.42	-.68

Table 5: Volatility of Model Variables

Standard deviations of Annualized Quarterly Growth Rates

	Standard Deviation		Difference
	I:60:1-79:4	II:84:1-00:1	(II-I)
GDP	3.98	2.13	-1.85
CPI Inflation	3.38	1.45	-1.93
Commodity Price Inflation	13.39	15.09	1.70
Federal Funds Rate (level)	2.63	1.99	-.64
Final Sales	3.14	2.11	-1.03
Inventories	3.21	2.82	-0.39

NOTES:

1. First period for inventories growth begins in 1967:2

Table 6: Results from 4-variable VAR

Stability Tests

Equation	Error Variance Stability F-statistic [marg. sig. level]	Coefficients Stability F-statistic [marg. sig. level]
Real GDP Growth	3.68 [.00]	1.32 [.18]
Inflation	1.12 [.34]	2.38 [.00]
Commodity Price Inflation	0.69 [.91]	0.96 [.52]
Federal Funds Rate	2.21 [.00]	0.78 [.72]

Standard deviations

Variable	Period 1: 1960:1-1979:4	Period 2: 1984:1-2000:1
Real GDP Growth	3.98	2.13
Fitted Value	2.36	1.41
Innovations	3.21	1.60
Inflation	3.38	1.45
Fitted Value	3.23	1.12
Innovations	1.00	0.90
Commodity Price Inflation	13.39	15.09
Fitted Value	7.47	7.98
Innovations	11.11	12.81
Federal Funds Rate	2.63	1.99
Fitted Value	2.56	1.95
Innovations	0.58	0.37

Table 7: Results from 5-variable VAR

Stability Tests

Equation	Error Variance Stability F-statistic [marg. sig. level]	Coefficients Stability F-statistic [marg. sig. level]
Final Sales Growth	2.95 [.00]	2.81 [.01]
Inventories Growth	1.78 [.04]	1.22 [.26]
Inflation	1.09 [.39]	2.96 [.00]
Commodity Price Inflation	0.90 [.62]	0.94 [.53]
Federal Funds Rate	4.15 [.00]	10.22 [.00]

Standard deviations

Variable	Period 1: 1967:2-1979:4	Period 2: 1984:1-2000:1
Final Sales Growth	3.38	2.11
Fitted Value	2.51	1.58
Innovations	2.26	1.39
Inventories Growth	3.28	2.82
Fitted Value	2.57	2.32
Innovations	2.03	1.61
Inflation	2.87	1.45
Fitted Value	2.72	1.14
Innovations	0.89	0.89
Commodity Price Inflation	15.58	15.09
Fitted Value	10.06	7.23
Innovations	11.90	13.24
Federal Funds Rate	2.40	1.99
Fitted Value	2.30	1.96
Innovations	0.67	0.35

Table 8: Results from 4-variable Monthly VAR

Stability Tests

Equation	Error Variance Stability F-statistic [marg. sig. level]	Coefficients Stability F-statistic [marg. sig. level]
Industrial Production Growth	2.81 [.00]	1.36 [.06]
Inflation	1.10 [.27]	2.25 [.00]
Commodity Price Inflation	0.74 [.97]	1.44 [.03]
Federal Funds Rate	2.42 [.00]	0.93 [.61]

Standard deviations

Variable	Period 1: 1960:1-1979:12	Period 2: 1984:1-2000:6
Industrial Production Growth	11.05	6.10
Fitted Value	7.23	3.71
Innovations	8.36	4.84
Inflation	3.47	2.18
Fitted Value	3.00	1.47
Innovations	1.74	1.61
Commodity Price Inflation	26.37	29.74
Fitted Value	14.23	16.13
Innovations	22.19	24.99
Federal Funds Rate	2.63	1.97
Fitted Value	2.61	1.96
Innovations	0.33	0.20

FIGURE 1

Real GDP Growth

Annual Rate

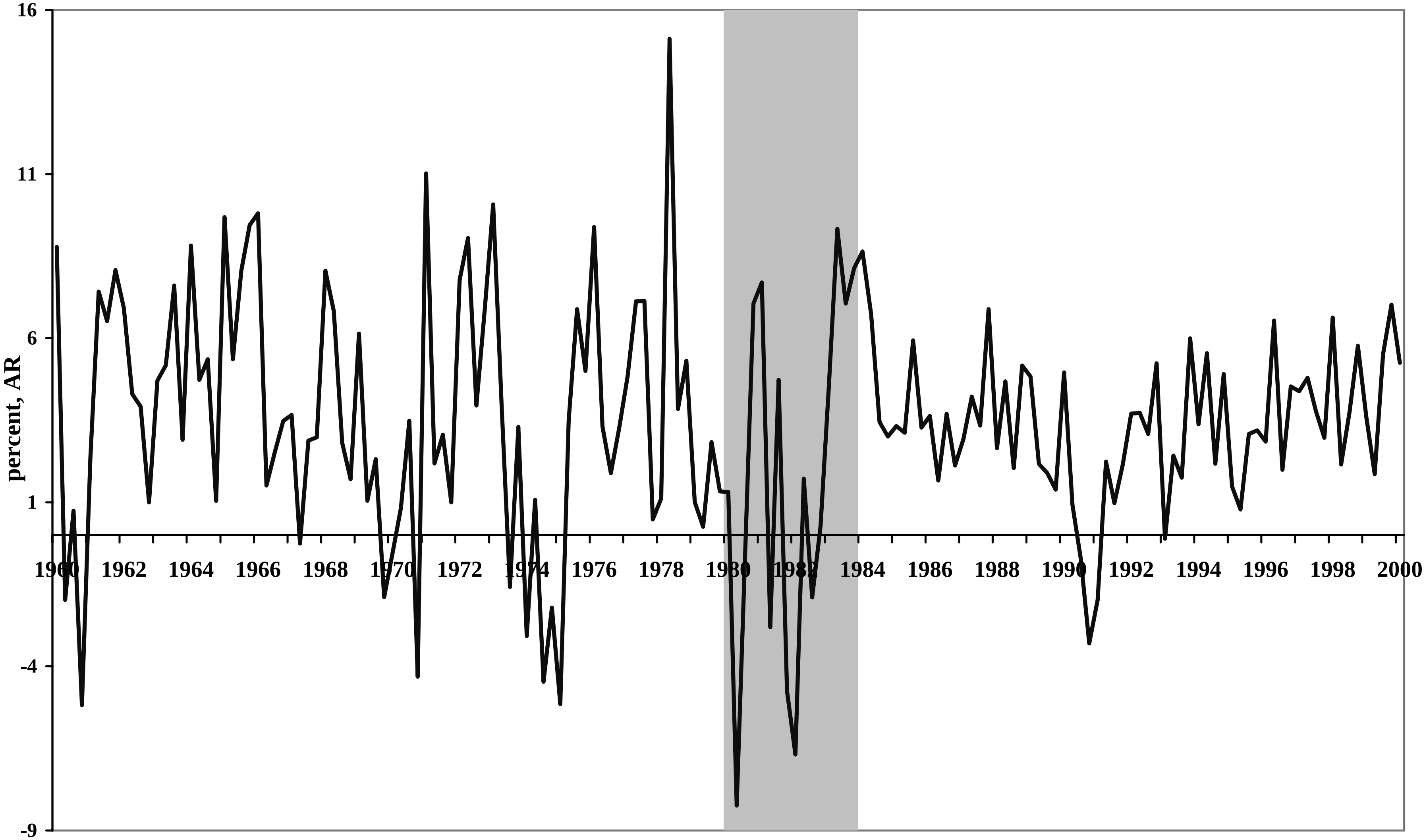

FIGURE 2

Components of Real GDP Growth

(annualized quarterly percent change)

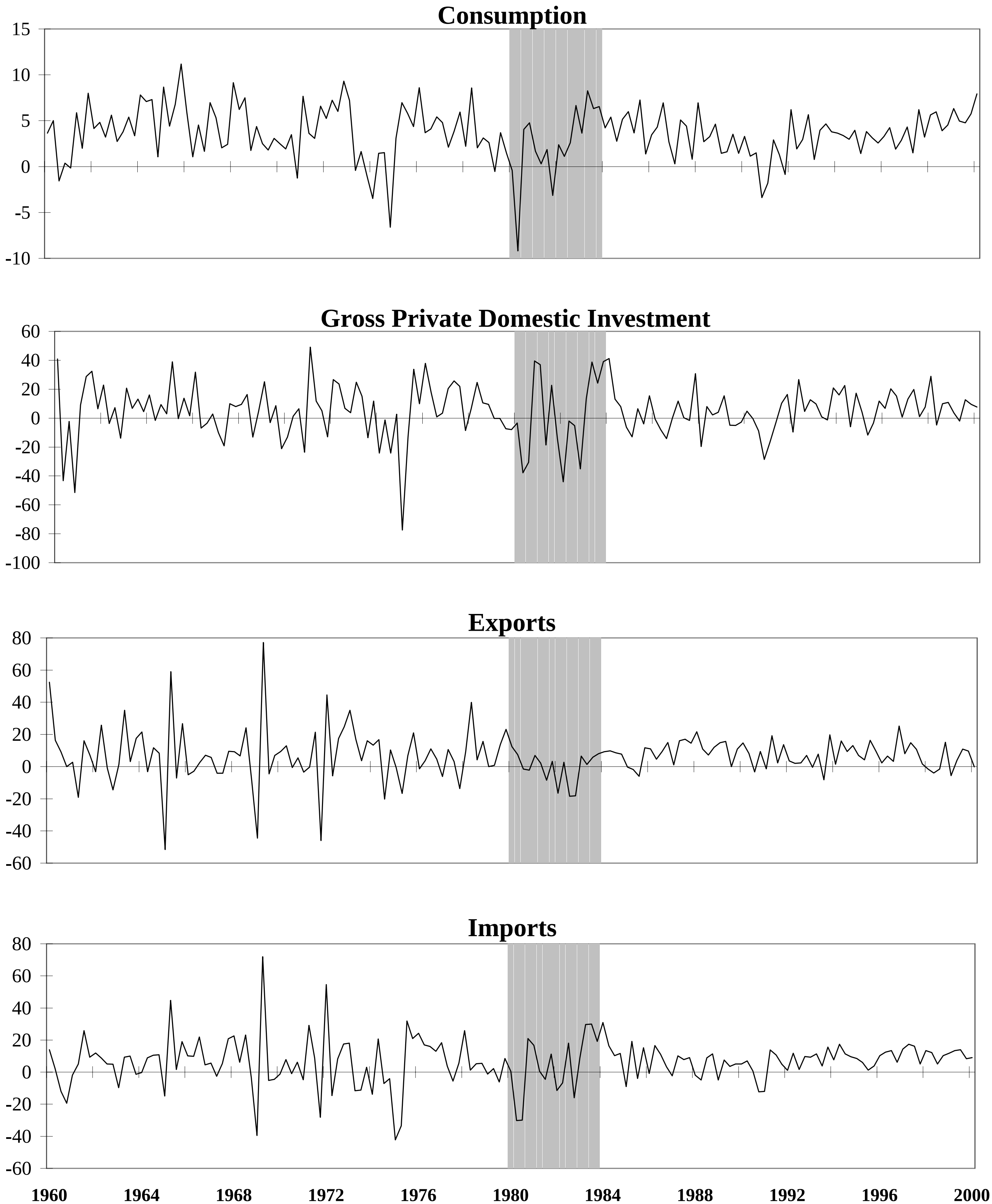

FIGURE 3

Components of Real GDP Growth (annualized quarterly percent change)

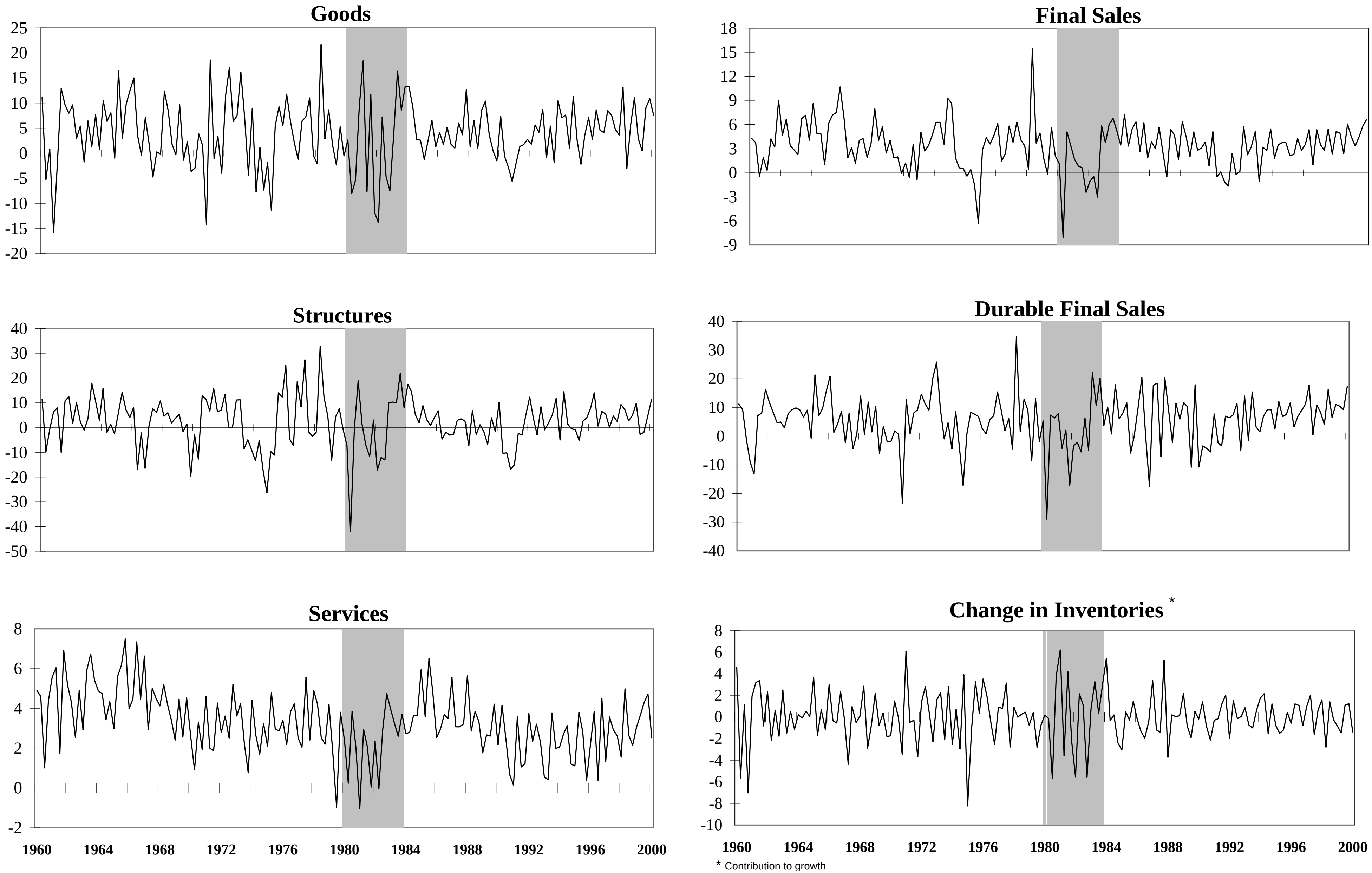

Figure 4

Plots of GDP growth

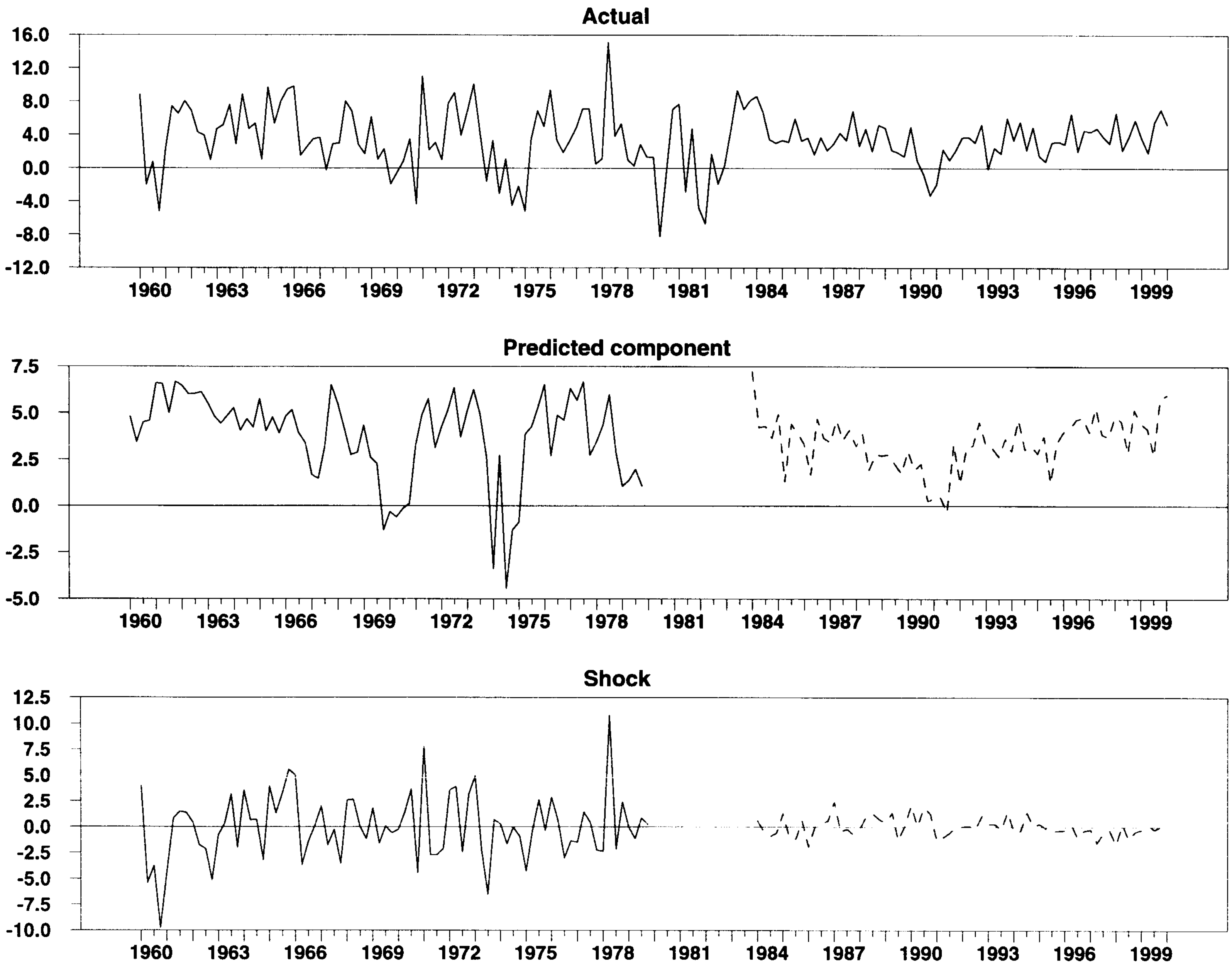

Figure 5

Plots of CPI Inflation

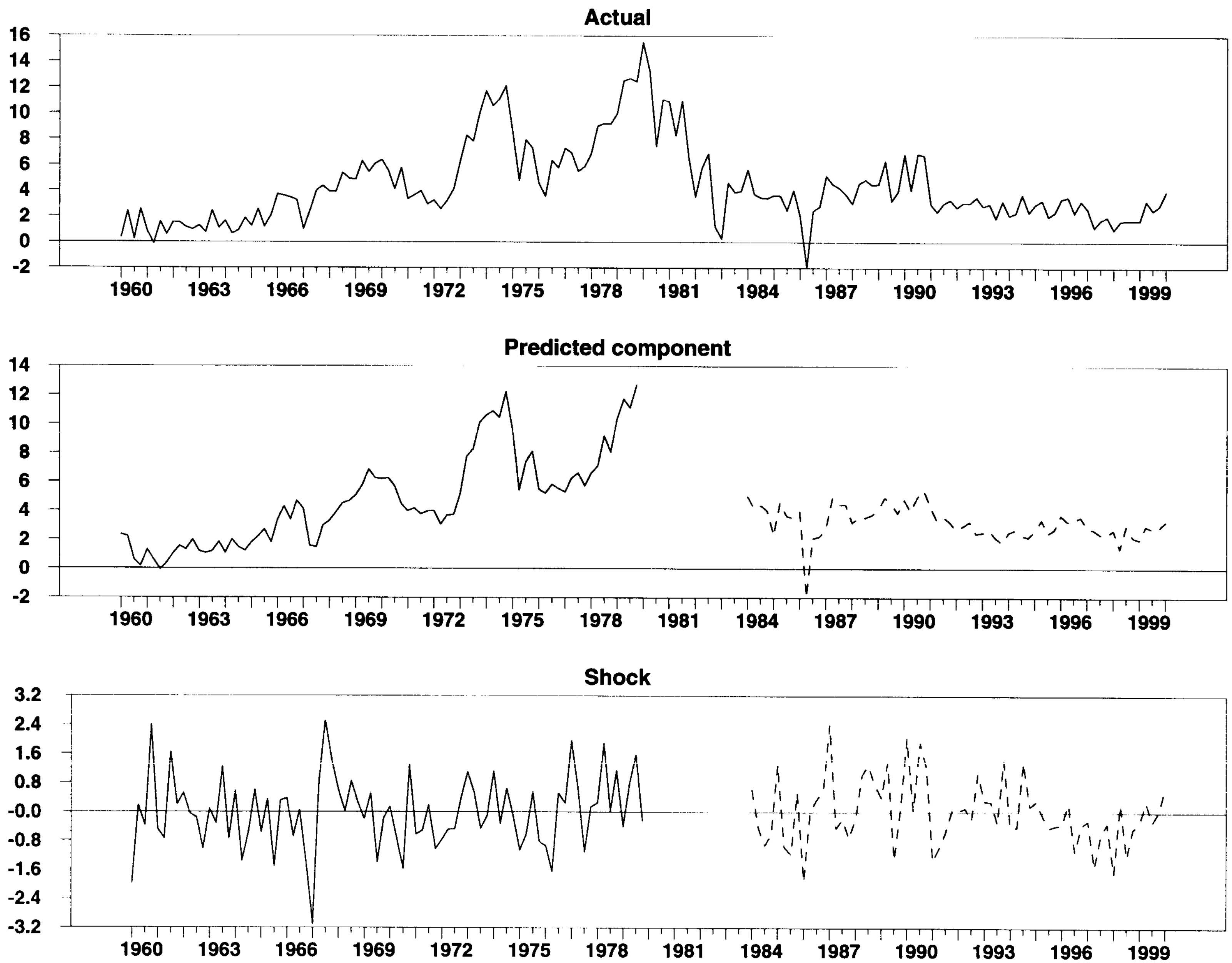

Figure 6

Plots of PC Inflation

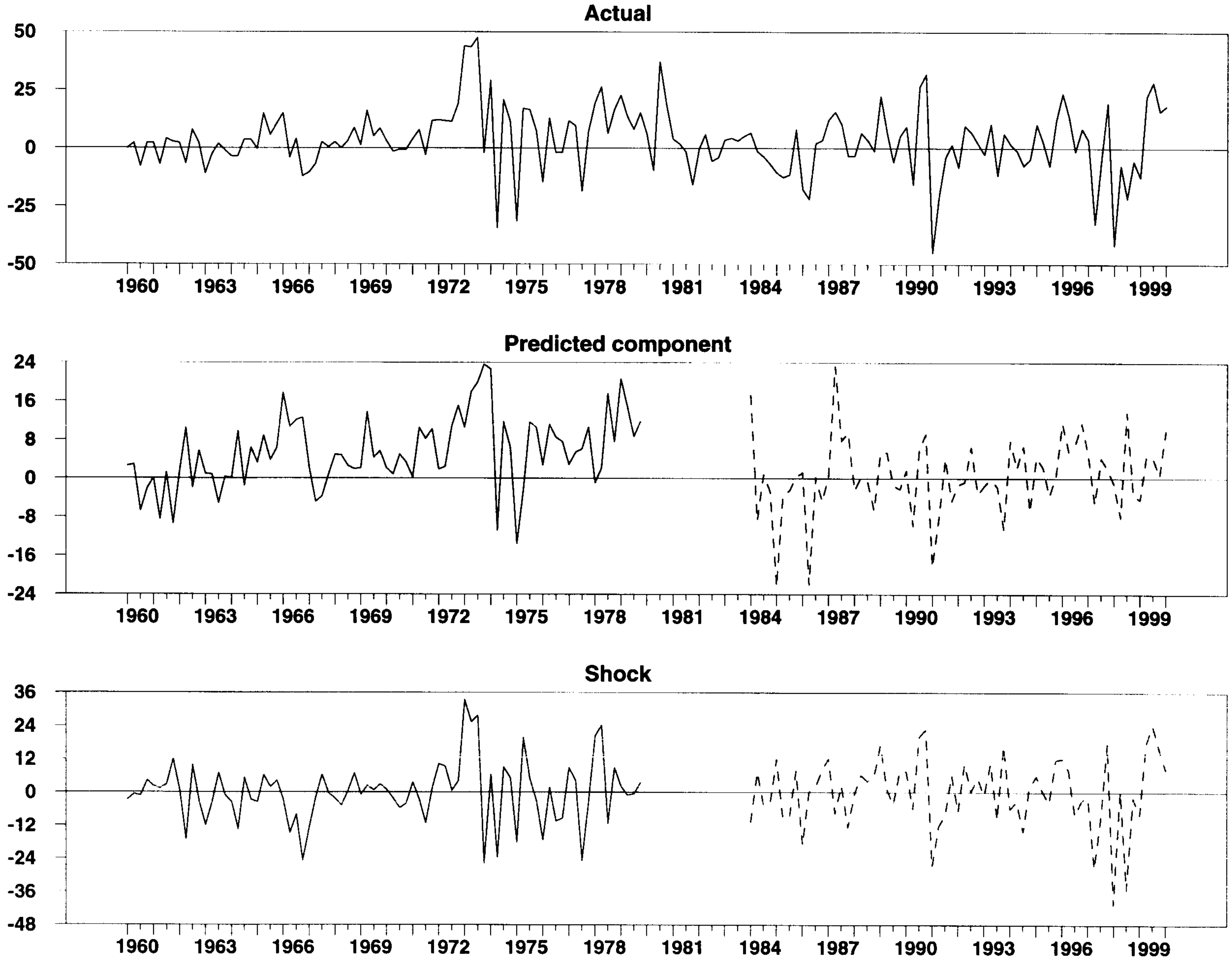

Figure 7

Plots of Fed. funds rate